IV. APPLICATION

The U.S. Environmental Protection Agency is now considering regulation of the arsenic emissions from the ASARCO smelter in Tacoma, Washington. Arsenic is a known human carcinogen and therefore emissions will be regulated under Section 112 of the Clean Air Act.

The E.P.A.'s first estimates of emissions from the major sources at the smelter are given in Table 3. (As the table indicates, these estimates have subsequently been revised twice.) As the table indicates, three control strategies are under consideration: no further control, BAT controls, and a limit on the arsenic content of the raw ore. It is believed that this last control strategy would lead to plant closure.

In support of the regulatory decision making process, the E.P.A. conducted a health risk assessment. Table 4 summarizes the results of their analysis of the aggregate health risks. These results are based upon the original E.P.A. emissions estimates.

A dilemma for the E.P.A. has been the disagreement between measured arsenic concentrations and concentrations estimated by the air pollution transport and dispersion models. For example, near the plant the model predicted annual average concentrations of about 30 $\mu g/m^3$. In contrast, the highest measured annual average concentration was 1.5 $\mu g/m^3$. Farther away from the plant the modelled and monitored values were in better agreement. For example, at the Vashon Island monitoring site, about 20 km North

Table 3. Arsenic Emissions from ASARCO (ton/yr)

Source	Controls	Original Estimate (8/83)	Second Estimate (11/83)	Current Estimate (3/84)
Main Stack	- current	165	57	57
	- BAT	170	59	58
	- closure	0	0	0
Converters	- current	132	34	17
	- BAT	7	2	1
	- closure	0	0	0
Other Fugitive	- current	14	24	34
	- BAT	14	24	34
	- closure	0	0	0

Notes:

(1) BAT assumes that 95% of the converter fugitive emissions will be captured by hoods and that the remaining 5% will continue to escape. Of the 95% captured by the hoods, 95% will be removed by air cleaning equipment and the remaining 5% will escape through the main stack, which is 585 feet (178 meters) high.

(2) The source of this table is an EPA Region X News Release dated 20 October 1983.

Table 4. Results of U.S. EPA Health Risk Assessment - Strategy A - No Additional Controls

Model: $R_i = \beta_1 \, d_i^1$

Estimate of Potency: (lifetime risk/unit dose) $\hat{\beta}_m = 3 \times 10^{-3}$

$\sigma_{\ln\hat{\beta}} = 2$

Life Expectancy: (yr) $\overset{o}{e}_o = 70$

Annualized Risk Coefficient: (annualized risk/unit dose) $\hat{\beta}'_m = 4.3 \times 10^{-5}$

Population at Risk: $N = 368{,}409$

Collective Dose to Population: (unit doses) $D = \sum_{j=1} N_j \, d_j = 104{,}850$

Estimate of Total Annual Population Risk:

$$\hat{R}_m = \hat{\beta}'_m \, D = 4.5$$

$$\hat{R}_{2.5\%} = \hat{R}_m / (\sigma_{g\hat{\beta}})^2 = 1.1$$

$$\hat{R}_{97.5\%} = \hat{R}_m \, (\sigma_{g\hat{\beta}})^2 = 18$$

Notes:

(1) The collective dose is governed by the 132 ton/yr estimate of emissions from the converters and the 14 ton/yr estimate of emissions from other fugitive emissions sources. It is based on exposures received within 20 km (12 mi) of the plant. Within this radius, the main stack contributes virtually nothing to exposures. The E.P.A.'s HEM was used in conjunction with the ISCLT dispersion model to produce these estimates. The estimated contributions to concentrations ($\mu g/m^3$) at several points of interest are given below:

Table 4 (continued)

Location	Distance from Source (km)	Strategy A	Strategy B
Ruston	0.3	17.0	6.09
	0.8	6.62	1.78
Tacoma	1.5	1.35	0.26
	4.4	0.30	0.05
	11.5	0.08	0.01

These data were taken from a letter by Joseph A. Tikvart to Robert L. Ajax, dated August 12, 1983.

(2) The E.P.A.'s potency estimate was derived from analysis of three epidemiological studies - Pinto (1977), Ott (1974) and Lee and Fraumeni (1969). The estimates of lifetime integrated relative risk at a $1\ \mu g/m^3$ continuous level of exposure given by application of a linearized multistage model to the data from these studies were 1.094, 1.170 and 1.033 respectively. When multiplied by the spontaneous U.S. lifetime lung cancer risk of 0.036 (1976, males), these correspond to lifetime potency estimates of 3.38×10^{-3}, 6.12×10^{-3} and 1.19×10^{-3}. To get estimates of annualized potency, these were divided by 70 years, yielding 4.83×10^{-5}, 8.74×10^{-5} and 1.70×10^{-5}.

(3) The central estimate of potency was simply the geometric mean of these three estimates:

$$\beta_1 \approx \left[4.83 \times 8.74 \times 1.70 \right]^{1/3} \times 10^{-5} = 4.3 \times 10^{-5}$$

(4) The estimated uncertainty in potency was also derived directly from these three potency estimates:

$$\sigma_{g\hat{\beta}} = e^{\left[\Sigma(\ln\hat{\beta} - \overline{\ln\hat{\beta}})^2 / (n-1)\right]^{1/2}} = 2.29$$

of the plant the monitored and modelled results were almost identical.

To illustrate our approach for estimating the value of improved exposure estimates we will examine this case as it appeared to the E.P.A. in the early Fall of 1983. Table 5 summarizes our estimates of the costs and health risks under the three alternative control strategies.

Our analysis is different from the E.P.A.'s in several ways. We assume that both proportional and quadratic dose-response models are plausible. The potency value used in our proportional model is three times as large as the estimate of potency used by the E.P.A. Our dose estimates are summarized in Table 6. We also have made a very approximate estimate of the cost of plant closure. The details of our analysis are explained in the notes to Table 5.

The analysis suggests that estimated aggregate cancer risks do not justify plant closure, but that, depending upon the model of cancer risk, the application of BAT may be appropriate. Anyone who assigns a probability of more than 0.04 to the proportional model, will come to the conclusion that BAT should be required.

The point of our analysis is not to recommend a control strategy for the ASARCO plant, but instead to indicate approximately the expected value of improved exposure estimates. Using a computer program, which we developed to evaluate expected opportunity losses, several estimates of the value of improved

Table 5. The Costs of ASARCO Control Strategies

Control Strategy	Control Cost (10^6/yr)	Health Risk (death/yr)		Expected Total Cost (10^6/yr)
		Proportional	Quadratic	
A - no add'l controls	0	17.5	1.05	17.5p + 1.05(1-p)
B - BAT controls	1.5	3.5	0.04	5.0p + 1.54(1-p)
C - plant closure	20	0	0	20

Notes:

(1) The annualized control cost estimate for the converter hoods of $1.5 million is made up of 0.86 million in annual electricity use (1.5×10^7 kwh/yr x $0.059/kwh). The source of this estimate is a letter from Clark Gaulding to Robert Ajax. In that same letter it is suggested that a more appropriate rate would be $0.0078/kwh (unit cost without demand charge) yielding an annualized control cost of $0.8 million.

(2) In estimation of total cost, lives were valued at $1 million.

(3) The annual cost of plant closure has been estimated very approximately as equal to the profits generated by the plant.

(4) The risks under a proportional model are assumed to be about three times those given by the low dose potency estimate from the linearized multistage mode. See Anderson (1983).

Table 5 (continued)

(5) The exposures in the three epidemiological studies were at least two orders of magnitude above the average ambient concentration of 0.3 $\mu g/m^3$ predicted by the HEM using the original emissions estimates. And we have assumed that the proportional and second order model yield equal estimate of risk two orders of magnitude above the typical ambient exposures, i.e., d_e 30$\mu g/m^3$.

(6) The application of BAT to the converters was predicted to reduce to collective dose to the population by 80%. See Tikvart (1983).

(7) The risk estimates made here are based on an estimate of the uncontrolled collective dose of ΣPd = 104,000 person - $\mu g/m^3$ per year and an estimate of the uncontrolled effective collective dose of Pd^2 = 172,000 person - $(\mu g/m^3)^2$ per year. See Appendix for details.

Table 6. Estimates of Collective Dose and Effective Collective Dose (N = Number Exposed = 368,548)

Interval	Fraction of Exposed Population	Concentration* ($\mu g/m^3$)	Squared Concentration ($\mu g/m^3)^2$
1	0.000024	32.2	1040
2	-	-	-
3	0.000581	13.8	190
4	0.002991	6.3	39.7
5	0.008519	3.1	9.61
6	0.034039	1.5	2.25
7	0.051821	0.70	0.49
8	0.130148	0.36	0.127
9	0.460780	0.15	0.0225
10	0.268864	0.08	0.0064
11	0.042233	0.095	0.0090

D_1 = collective dose = $N \sum_{j=1}^{11} w_j d_j = 1.04 \times 10^5$ ($\mu g/m^3 \cdot$person)

D_2 = effective collective dose = $N \sum_{j=1}^{11} w_j d_j^2$

$= 1.72 \times 10^5$ $(\mu g/m^3)^2 \cdot$person

*These estimates of concentration are from the ISCLT model and the original emissions estimates.

exposure estimates were derived. The estimated expected opportunity losses include two components, one due to model uncertainty, the other due to parameter uncertainty. The results are summarized in Table 7.

The analysis indicates that depending upon the degree of confidence a person had in the proportional dose-response model, he should have been willing to pay up to 203 thousand dollars per year to resolve the uncertainty about exposure. Those who were at all uncertain about the form of the model would have been willing to pay larger sums to find out which dose-response model was correct.

Of course within the time interval available for further analysis it will not be possible to determine which dose-response model is correct. However through further monitoring and modelling it may be possible to reduce the uncertainty surrounding the exposure estimates. If one believes that the control strategy about to be selected will be in place for twenty years, then the present value of the stream of expected opportunity losses is an appropriate measure of the value of information. Using a real discounting rate of 5% per annum one would conclude that it would be worth up to $2.50 million dollars to know exposures perfectly.

Because many of the parameter values and assumptions of our analysis are themselves uncertain these specific numerical results should not be over interpreted Table 8, which summarizes the results of several sensitivity analyses, is provided to give the reader some sense of the stability of the estimates.

Table 7. Expected Opportunity Losses ($\$10^6/yr$)

P	EVPEI	EVPMI
1.0	0.024	0
0.75	0.003	0.090
0.50	0.003	0.180
0.25	0.027	0.270
0	0.203	0

Notes: (1) P = probability that proportional model is correct

(2) EVPEI = expected value of perfect exposure information

(3) EVPMI = expected value of perfect model information

Table 8. Sensitivity Analyses for Proportional and Quadratic Models

Parameter	Elasticity of EVPEI*	
	Proportional Model	Quadratic Model
Cost of BAT	+ 0.3	- 1.7
Cost of Closure	- 3.9	0
Value of Life	+ 6.6	+ 2.7
Efficiency of Bat	- 16.1	+ 0.8
Median Potency Estimate	+ 6.6	+ 2.7
Standard Geometric Deviation of Potency Estimates	+ 3.6	+ 1.9
Median Collective Dose or Collective Effective Dose	+ 6.6	+ 2.7

*An estimate of $\frac{df/\bar{f}}{dx_j/\bar{x}_j}$ calculated numerically by perturbing x_j by +5% and reevaluating f.

Apparently the results are quite sensitive to the values chosen for the efficiency of BAT, value of life, median potency, and median collective dose.

Because our estimates of the cost of plant closure and of the uncertainty in the original estimate of collective dose are very soft, the entire analysis was repeated for several alternative estimates of these parameters. The results are summarized in Table 9. It is evident that if the cost of plant closure is lower than we originally estimated, the value of improved exposure estimates is much greater than our first estimates. Similarly, if the 95% confidence interval for the original collective exposure estimate spans more than a factor of 4 (i.e. $\sigma_g > 2$), then the value of improved exposure estimates is several times larger than our original estimates.

In summary, our analysis indicates that although the key source of uncertainty in the ASARCO risk analysis is model uncertainty, parameter uncertainty may also contribute significantly to expected opportunity losses. And further, that although the expected opportunity losses due to parameter uncertainty are not large relative to the total costs of the control strategies, they are large in comparison with the costs of environmental monitoring and modelling efforts which could be expected to substantially reduce the uncertainty in current estimates of exposure.

Most good analysis is sequential. These preliminary results are encouraging and suggest that a more precise analysis of the ASARCO case might be warranted.

Table 9. Estimates of the Expected Value of Perfect Exposure Information Alternative Values of the Estimated Cost of Plant Closure and of the Uncertainty in the Original Exposure Estimate

Cost of Closure = $20x10^6$/year

Probability that Proportional Model is Correct, P	Uncertainty in dose, σ_g		
	1.4	2.0	3.2
1	0.000	0.024	1.119
0.5	0.000	0.003	0.251
0	0.015	0.203	0.592

Cost of Closure = $5x10^6$/yr

Probability that Proportional Model is Correct, P	Probability that Proportional Model is Correct		
	1.4	2.0	3.2
1	0.428	0.694	0.940
0.5	0.098	0.271	1.434
0	0.015	0.203	0.592

*Factor to within which collective dose is thought to be known, $(e^{\sigma_{\ln \hat{D}}})^2$, i.e., 95% confidence interval.

V. CONCLUSIONS

This paper has illustrated how the method of statistical decision analysis can be applied to estimate the value of information in support of environmental decision making. Through a combination of hypothetical examples and a case study we have demonstrated how to estimate economic opportunity losses and how to use these estimates to determine the value of improved exposure estimates. Finally, we have shown that the estimated value of information depends upon both model uncertainty and the uncertainty in other parameters critical for decision making.

Although in many cases the resulting estimates may not be as robust as one would like, they may still be useful for establishing bounds on the value of information. In some cases these bounds may permit clear resolution of the question ... "Should we decide on the basis of current information or should we wait to decide until additional information is obtained?"

APPENDIX

Although for some decisions it may be important to estimate the entire distribution of risks in the exposed population, here the analysis is limited to estimation of the total population risk:

$$R = \sum_{i=1}^{N} R_i \qquad \text{(A-1)}$$

whereas R_i is the lifetime integrated risk to the i^{th} individual and N is the number of persons at risk. Further simplification is achieved by:

(a) assuming that the population at risk is stationary with an age distribution similar to that of the current U.S. population:

(b) assuming that the conditions of exposure are at equilibrium and are constant throughout the period of interest:

(c) assuming, therefore, that the number of deaths in any geographic cell is constant and equal to the product of the number of people in the cell and the lifetime integrated risk appropriate for that cell; and

(d) assuming that the geographic cells are small enough that dose is essentially constant throughout each cell.

Under these assumptions, the total population risk (cases/year or deaths/year) is:

$$R = \frac{1}{e_o} \sum_{j=1}^{m} N_j \, R(d_j) \qquad \text{(A-2)}$$

where N_j is the number of persons exposed to a lifetime integrated dose of d_j in the j^{th} geographic cell, $R(d_j)$ is the lifetime integrated risk for a biologically average individual receiving a dose d_j, and e_o is the life expectancy at birth (years) of the average person in the population.

To illustrate how aggregate risks are estimated, consider the simple case in which risk is proportional to dose:

$$R_i = \beta d_i \qquad \text{(A-3)}$$

where β is the constant of proportionality relating dose to risk for the biologically average individual. Here the total population risk becomes:

$$R = \frac{\beta}{e_o} \sum_{j=1}^{m} N_j d_j \qquad \text{(A-4)}$$

If we substitute D for $\sum_{j=1}^{m} N_j d_j$, the collective dose to the population, and β' for β/e_o, the annualized risk coefficient, we have:

$$R = \beta' D \qquad \text{(A-5)}$$

According to some models of cancer induction, risk is proportional to some higher power of dose:

$$R_i = \beta_k d_i^k \qquad k \geq 1 \qquad \text{(A-6)}$$

For these models to give similar estimates of risk in the region of doses observed in epidemiologic studies the parameters β_1 and must be related:

$$\beta_k = \frac{\beta_1}{d_e^{k-1}} \qquad \text{(A-7)}$$

In this more interesting and complex case the total population risk is:

$$R = \frac{\beta_k}{e_o} \sum_{j=1}^{m} N_j d_j^k \qquad \text{(A-8)}$$

Here again we can substitute D_k for $\sum_{j=1}^{m} N_j d_j^k$, the effective collective dose to the population, and proceed as we did above.

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PART 11

THE VALUE OF AQUIRING INFORMATION UNDER SECTION 8(a) OF THE TOXIC SUBSTANCES CONTROL ACT: A Decision-Analytic Approach

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I. INTRODUCTION

The Environmental Protection Agency (EPA) faces major uncertainties in making regulatory decisions about toxic or potentially toxic substances. Much of the regulatory process may be viewed as a series of efforts to acquire information that reduces those uncertainties and leads to better decisions. To strike the appropriate balance between protecting human health and the environment on the one hand, and avoiding the imposition of unnecessary regulatory burdens on the other, EPA needs information on a wide range of subjects, including toxicity, exposure, and the costs of alternative control options. Typically estimates of these parameters are refined over time.

EPA obtains its information through a wide variety of mechanisms. Early in the process, major reliance may be placed on literature reviews and informal contacts with relevant experts. At later stages, more detailed and costly methods may be used, including surveys of potentially affected firms, engineering studies of control options, detailed exposure modeling and monitoring, and analyses of the economic impact of

alternative regulations. Before a regulation is formally proposed, usually a great deal of information has been acquired, although substantial uncertainties almost always remain. After proposal, still more information is acquired, through hearings, written comments from outside parties, and other means. Before promulgating a final rule, EPA may commission additional studies to update the information and to respond to comments and criticisms.

The focus of this report is on one statutory means of obtaining information -- Section 8(a) of the Toxic Substances Control Act (TSCA). Section 8(a) gives the Administrator of EPA authority to promulgate rules requiring that chemical manufacturers and processors provide several types of information to the Agency, including the names of chemicals, their uses, volumes produced or processed, existing data that firms have on adverse health or environmental effects, and the numbers of people exposed. All requests are subject to the requirement that the information be "reasonably ascertainable."

The information that can be obtained under Section 8(a) is of substantial potential value, particularly as some of the information may be proprietary and thus not obtainable through other means. Indeed, in some cases the information might be crucial in deciding whether to regulate, what regulatory strategy to employ, or how stringent the regulations should be. But information is not costless to obtain, whether it be under the authority of Section 8(a) or by other means. The total cost of information acquisition in major rule makings easily can run to millions of dollars. A single study, say to test toxicity or to

perform a detailed engineering analysis of control options, may cost hundreds of thousands of dollars. Thus, the decision whether or not to gather information merits attention and analysis. General arguments in favor of considering the costs and benefits of information are reinforced in the case of Section 8(a) because it involves the promulgation of a formal rule that potentially is subject to the requirements of Executive Order 12291.

The logical conceptual framework in which to estimate the value of information is decision analysis, a method for structuring and evaluating decisions under uncertainty. Decision analysis provides a clear and intuitively appealing definition of the value of information; it is the expected improvement in the value of the objective function from having the information available before decisions are made. For the purposes of this paper, we take EPA's objective function to be the maximization of expected net benefits. Although EPA's statutes contain many different decision criteria, this benefit-cost criterion is consistent with the aims of Executive Order 12291 and with a common, though far from universal, interpretation of "unreasonable risk" under TSCA (e.g., see North 1982).[1]

Decision analysis provides a coherent, flexible framework in which to estimate the value of information. Many practical problems arise, however, in applying it to real decisions. To explore those problems, and to illustrate how decison analysis can be used to evaluate potential 8(a) rules, much of this report consists of a case study of a particular rule that was drafted

but never formally proposed. That rule would have required manufacturers and processors of ethylene dichloride (EDC), a proven animal carcinogen, to report on the amounts employed in "dispersive uses," uses in which most or all of the substance is released to the environment.

This report is organized into six chapters, including this one. Chapter 2 focuses specifically on Section 8(a), discussing its advantages and disadvantages (relative to other methods of gathering information), potential problems with the accuracy of information obtained under 8(a), and various ways in which that accuracy might be improved. Chapter 3 provides a brief introduction to decision analysis and addresses some of the problems involved in using the technique to estimate the value of information acquired on toxic substances: readers already familiar with decision analysis may wish to skip this chapter. Chapters 4 and 5 comprise the case study of dispersive uses of EDC; Chapter 4 provides an overview of existing information, while Chapter 5 develops and applies a decision-analytic framework. The final chapter presents our conclusions and recommendations, drawing on both the case study and the more general analyses of chapters 2 and 3.

II. SECTION 8(a) OF TSCA

Section 8(a) is one of several methods the EPA has for obtaining information on chemicals. Alternatives include consultants' reports, voluntary surveys, literature reviews, and other sections of TSCA that allow the Agency to obtain information. In the seven years since TSCA was passed, the EPA has promulgated only four Section 8(a) rules. The first two covered Tris and PBBs (45 Fed Reg 70728 1980). Those two rules, however, were very minor in scope, as production of both chemicals had ceased in the U.S. The rules required that manufacturers notify EPA if they resumed production. More recently, EPA promulgated the "Level A" rule on June 22, 1982; it requires manufacturers and importers to report information on a list of about 250 chemicals (47 Fed Reg 26998 1982). This information includes production quantities, the types of processes in which the substance is used, and the numbers of workers exposed. The fourth rule, which was promulgated on July 30, 1982, is targeted at producers and processors of asbestos (47 Fed Reg 33206 1982). (We describe that rule in greater detail later in this chapter.) Thus, to date Section 8(a) has not been a major means of collecting information on toxic substances.

In this chapter, we evaluate the Section 8(a) process as a mechanism for gathering information. This chapter serves both to provide some perspective on why Section 8(a) has been used so infrequently and to introduce the detailed case study of EDC that follows in Chapters 4 and 5. The first section discusses the

advantages and disadvantages of a Section 8(a) rule. We conclude that Section 8(a) may be of limited usefulness, with its greatest comparative advantage in gathering information on quantities and uses. Other means are likely to be superior for collecting other data. The next section discusses the 8(a) rule for asbestos. The asbestos example serves to illustrate the limitations of the Section 8(a) approach and to indicate ways the Agency has attempted to overcome these limitations. The final section summarizes the chapter.

Advantages and Disadvantages of Section 8(a)

The ideal information-gathering mechanism would provide accurate data on a wide range of subjects in a timely, inexpensive manner. Although no approach can satisfy all of these criteria, they do suggest some useful categories for evaluating the relative advantages of the 8(a) process: (1) the range of information that can be collected; (2) the accuracy of the information; and (3) its costs and delays.

Range of Information. The range of information that can be requested under Section 8(a) is broad. The statute specifically lists volumes and uses, byproducts, health and environmental effects, exposures, and the manner of disposal. EPA interprets this authority to include, in addition, data on the concentrations to which workers are exposed, emission levels, customer lists, and other information.

It is clear, however, that Section 8(a) is not equally useful for obtaining these various categories of information. Firms are only required to report information "insofar as known to the person making the report or insofar as reasonably ascertainable." Thus, data that are difficult or costly for firms to provide are not covered by 8(a). The 8(a) process is unlikely to prove very useful in gathering new information on toxicity or adverse environmental effects, as 8(a) rules are limited to requiring that firms supply existing studies on those subjects. Few firms are likely to have such studies that have not been made public.

In contrast, Section 8(a) is likely to be a good means of acquiring information on volume and use. Firms are likely to have such information readily available, at least for their own activities and those of their major customers. Detailed data on volumes and uses for individual plants also can be combined by EPA with estimates of emission rates and exposure factors to generate at least rough estimates of the benefits of regulatory options. A Section 8(a) rule also may be of value simply because it alerts EPA to particular classes of uses that had not been identified through other means.

Accuracy of Information. In theory, a Section 8(a) rule generates very accurate information because the data are provided directly by firms, and all firms covered by the rule are legally compelled to respond. Unlike voluntary surveys or informal contacts, Section 8(a) rules carry the force of law, with firms that fail to respond or that provide false information subject to

civil and criminal penalties under Section 16 of TSCA. In practice, however, we believe that the accuracy of the information provided by an 8(a) rule will be far from perfect.

One difficulty is that a Section 8(a) rule is unlikely to cover all of the relevant firms. Section 8(a) does not allow EPA to require reports from end users or distributors unless they also are "processors" (which can mean that they simply repackage the material). This limitation may pose serious problems for getting information on small-volume users who purchase the product from distributors. As discussed in Chapter 4, for example, consultants had a difficult time getting information on dispersive uses of EDC in part because customers for such uses typically do not deal directly with manufacturers, but rather buy from distributors. This same fact, however, could limit the usefulness of a Section 8(a) rule.

In addition to statutory limitations, EPA also may choose to exclude "small" firms from an 8(a) rule. Although such exclusions are desirable from the perspective of limiting reporting burdens, they introduce additional uncertainty into the estimates, particularly if the Agency does not have reliable data on the fraction of total volume for which small firms account. To the extent that small firms differ in systematic ways from those covered by the rule, projections based on an 8(a) rule may suffer from additional inaccuracies.

Even among firms covered by a Section 8(a) rule, the response rate may fall far short of 100 percent. In some cases, EPA can identify individual firms and send them the necessary forms and notification of the rule. Many firms may be missed,

however, and EPA must rely on the Federal Resister and trade publications to inform them of their obligation to submit information. Some firms, particularly smaller ones, will not see such notices, or will mistakenly conclude that the rule does not apply to them. Three to six months after the Occupational Safety and Health Administration (OSHA) promulgated a highly publicized standard for asbestos in the workplace, for example, Schoenberg and Mitchell (1974) interviewed officials of 24 companies subject to that regulation. Of the 24 firms, only eleven were familiar with the standard's requirements. Another ten merely had heard of it, but did not know its provisions. Three firms were not even aware of its existence. As the requirements of a Section 8(a) rule are likely to be relatively simple, we suspect that a smaller fraction of firms will be in the intermediate category. We also suspect, however, that a substantially larger fraction than in the Schoenberg and Mitchell study will be totally unaware of the rule.

Even among those firms that become aware of an 8(a) rule, not all will respond. They may fear that confidential information will be released accidently, or they simply may wish to avoid the time and expense of obtaining the forms and filling them out. Although EPA is authorized under Section 16 of TSCA to seek fines of up to $25,000 per violation per day, firms may reason (probably correctly) that the probability that nonreporting will be detected and penalized is low. We expect this problem to be more important for small firms than for larger ones. On balance, however, we speculate that conscious

nonreporting will be a less serious source of incomplete coverage than simple ignorance of the rule.

The value of Section 8(a) information also may be reduced because of inaccurate reporting by the firms that do respond. To save time and effort, firms may simply report a crude estimate rather than undertake a careful search of their records. This is likely to less of a problem for basic information on volume and use than for more complex and judgmental data on potential exposures and the like. It is likely to be more severe when firms are asked to report on the activities of their customers as well as their own. Intentional misreporting is also a possibility, though we suspect a much smaller one than lack of care.

Cost and Delay. Acquiring information under Section 8(a) is likely to incur higher costs and more delay than other methods because it requires promulgating a formal rule, and thus is subject to a variety of administrative and procedural requirements that do not apply, for example, to hiring a consultant. Indeed, one of the motivations for this study is the requirement under Executive Order 12291 that rules be subjected to a benefit-cost analysis. Section 8(a) rules may also require more resources in the form of public hearings, public comments, and other expenses of the rulemaking process.

Timing may account for a major difference between a Section 8(a) rule and other mechanisms for acquiring information. The rulemaking process -- internal Agency decision to propose the rule, public hearings, public comment period, review under

Executive Order 12291, final decision, and litigation -- can be time consuming even for relatively modest rules. For example, the Agency spent almost three years developing the Section 8(a) rule for asbestos. But the timing issue should not be overstated. Even a voluntary survey must be approved by the Office of Management and Budget, a process that can take as much as a year.

The Asbestos Section 8(a) Rule

The EPA's preliminary experience with the Section 8(a) rule for asbestos provides a useful means of comparing Agency experience with our a priori evaluation. Our analysis suggests that 8(a) rules are likely to have their greatest comparative advantage in obtaining information on production and use, and that the greatest difficulty will be in assessing the completeness of the response of firms to the request. Both predictions are borne out by the asbestos rule. The EPA's handling of the asbestos rule also illustrates some of the options the Agency has to improve reporting, although it is too early to assess their success.

The Asbestos Rulemaking.[2] Before deciding to propose a Section 8(a) rule for asbestos, EPA had gathered information from a variety of sources, including voluntary industry reporting, published sources, data collected by other Federal agencies, and its own contractors. EPA believed that this information was not sufficiently complete and up-to-date, however. The Agency identified the following gaps in its regulatory data base: (1)

limited and incomplete data on the types of products made with asbestos; (2) almost no information on the location of many firms using asbestos; (3) inaccurate and highly aggregated data on quantities of products containing asbestos; (4) inadequate and unrepresentative data on the number of employees exposed and their exposure levels; (5) little information on asbestos wastes and industry waste disposal practices; and (6) limited information on current pollution control practices. EPA stated that almost all of its data were several years out of date and that conditions in industries using asbestos had been changing rapidly. It also indicated that further voluntary submission of data by industry and contractor studies would not substantially improve the data:

> Contractors working for various OPTS offices have had difficulty in obtaining new data. Often, information is withheld by industry because it is considered proprietary. Many requests to industry for information have gone unanswered or resulted in the submittal of information of little value. Sometimes entry to manufacturing and processing facilities to perform independent monitoring has been either denied or delayed (46 Fed Reg 1981, 8202)

A final 8(a) rule for asbestos was published on July 30, 1982 (47 Fed Reg 33206 1982). This rule required all "primary processors" (firms which process bulk asbestos), mines, mills, and importers of bulk asbestos to report by November 29, 1982 data on volumes by use of asbestos, number of employees, worker exposures, emissions, disposal of wastes, and pollution control equipment. Importers of asbestos mixtures and "secondary processors," whose raw materials are asbestos mixtures or processed asbestos, were required to report by October 29, 1982 data only on volumes and uses of asbestos and asbestos products.

The rule contained provisions to require more complete reporting by a sample by secondary processors at a later date.

Notification. The Agency used several methods to notify firms of the Section 8(a) rule. In addition to the Federal Register and trade publication notices, EPA also developed a program to notify firms by mail that they might be subject to the rule. An EPA contractor (GCA) developed a mailing list of firms in the 55 4-digit SIC codes identified as likely to use asbestos. The contractor assembled the names and address of all 70,000 firms in these industries listed by Dun and Bradstreet. This list clearly included many more firms than the 6,000 that EPA had estimated were subject to the rule, and EPA decided that it was too costly to notify all of them by mail. One option would have been to send notices to a sample of firms on the full list. Instead, EPA chose a small number of industries that were known to have a high proportion of asbestos primary processors, and notified all 3,200 firms in those industries. EPA anticipated, however, that many other firms would learn of the rule and request forms.

Follow-up on Non-Respondants. One means of assessing the completeness of reporting under Section 8(a) is to compare totals to those obtained from other sources. If the totals are approximately equal, it may be reasonable to infer that the detailed estimates are accurate. Data on the total quantity of

chemicals produced are available from trade publications such as Chemical and Engineering News, government agencies, or private business services such as SRI's Chemical Economics.

EPA compared the total volume of asbestos use reported by "primary processors" to an estimate prepared by the U.S. Bureau of Mines from surveys. The Section 8(a) totals represented approximately 90 percent of that estimate, which suggests that reporting by primary processors was reasonably complete. Since the Bureau of Mines believes that the actual volume may be 50 percent greater or less than its best estimate, however, this inference is itself uncertain. Moreover, even if 90 percent of the total volume is accounted for, the Section 8(a) estimates of emission and exposure may be biased downward if firms with high emissions or employee exposure are less likely to report.

As of March 1983, the Agency had only incomplete information on the results of the mailing to firms. Of the 3200 forms mailed out, approximately 700 had been returned by the Post Office as undeliverable and 1200 firms had written to tell EPA that they were not covered by the rule. There had been 820 submissions, but EPA did not know how many of those were from firms on the mailing list. (If all 820 were mailed notices, then there were about 500 non-responses.)

Of the 820 submissions, 515 were from secondary processors. Since EPA had expected almost 6000 responses from this group, it was concerned that there was considerable non-reporting. As a result, the Agency took two actions. First, it hired a contractor (Westat) to evaluate the responses of the firms that were mailed notices of the rule, but did not submit the required

data. This study could identify the response rate among the 3200 firms. If non-respondants who were identified as subject to the rule then submitted the required data to EPA, data on their volume, uses, emissions, etc. would be complete. However, since the list was not chosen randomly or chosen to be representative of the list of 70,000 firms, neither the response rate nor the data reported are representative of all firms subject to the rule. Unbiased estimates of total volume by use, employees exposed, emissions, waste disposal, etc. generally will not be possible.

The 8(a) rule itself can be used to generate extra information about companies that use the hazardous chemical. Customer lists can be requested of producers and processors of the chemical. These lists can be used for a second mailing to notify firms of the rule or in attempts to verify completeness of reporting. The proposed Section 8(a) rule for asbestos contained just such a requirement. Primary processors of asbestos would have been required to keep a list of their 1980 customers and the quantity of asbestos-containing products sold to each, and to provide EPA with that information on request. This requirement was deleted from the final rule largely because of the strong objections of the asbestos industry, which complained that leaks of this information might be harmful.

After it received responses to the rule, EPA decided to identify the large primary processors and request customer lists from them under its Section 11 inspection authority. Using those lists, it planned to contact customers to see if they had

reported and if they were required to report. The results of this study were to be generalized to the universe of covered firms to derive an estimate of total asbestos volume in its various uses.

Conclusions

Section 8(a) appears to allow EPA to collect a variety of useful data from the most knowledgeable, least-cost source -- firms that manufacture or process potentially regulated substances. The usefulness of Section 8(a) is limited, however, by several factors, including the statutory requirement that data be "readily available." Data on health and environmental affects, on environmental emissions, and on occupational exposure may not be "readily available." Because of this, the comparative advantage of Section 8(a) rules is likely to be limited primarily to collecting volume and use data.

Even for volume and use data, Section 8(a) must be used with care. The fact that end users and distributors are not subject to reporting may make it difficult to get complete information. Because rulemaking procedures must be followed, promulgating a Section 8(a) rule is likely to be time-consuming and expensive. Finally, although firms are required to report and may face penalties for not reporting, there is likely to be substantial underreporting, especially by smaller firms. Because of these limitations, Section 8(a) may be valuable in only a small number of circumstances, when other methods have been exhausted and when volume and use information is particularly important to collect.

III. DECISION ANALYSIS AND THE VALUE OF INFORMATION

Decisions about gathering information are made, almost by definition, under conditions of uncertainty. Decision analysis offers a formal framework for structuring decisions under uncertainty and, more specifically, for estimating the value of information. It treats information as part of a sequential process of decision making, in which information is represented as the resolution of uncertainties before choices must be made. The value of information in decision analysis is the improvement it yields in expected net benefits.

The techniques of decision analysis have been developed and refined over the last two decades. Although originally developed for financial decisions, decision analysis has been applied to a wide variety of problems, ranging from clinical decisions about alternative medical treatments (e.g., see Bunker, Barnes, and Mosteller 1977), to strategies for resolving uncertainty about the effects of stratospheric flight on ozone depletion (Zeckhauser, Shearer, and Memishian 1975). Of more direct relevance to this study, decision analytic concepts have been used to explore ways in which testing strategies for potentially toxic substances could be improved (Weinstein 1979), and decision analysis has been suggested as an aid in the determination of "unreasonable risk" under TSCA (Campbell, Cohan, and North 1982).

In a decision analytic framework, information does not have intrinsic value. Its value springs, instead, from its potential ability to change decisions, which in turn affect outcomes. Thus, estimating the value of information requires that one determine what decision(s) would be made in the absense of the information and how different results from the information-gathering process could alter those decisions. Typically the decision tree must be integrated with a model of benefits and costs to compute the net benefits of different outcomes.

Information also may have value for other reasons. Decision makers, for example, may feel more confident or comfortable with more information, even if it has no impact on the decisions they make. Legal or administrative requirements may compel the gathering of information before particular choices can be made. In some cases such considerations can be incorporated into the analysis, either by modifying the objective function or by adding constraints (e.g., an option cannot be chosen unless a study of its economic impact is undertaken). Our analysis in Chapters 4 and 5 implicitly includes some of these considerations in the form of promulgation costs that account for procedural requirements.

In this chapter, we sketch out some of the issues involved in using decision analysis to estimate the expected value of information on toxic substances being considered for regulation. The first section uses a simple example to present the bare essentials of the process and to highlight some basic principles. It is not meant to be a comprehensive treatment of the many technical issues involved in performing a decision analysis;

readers interested in a more detailed treatment should consult either a standard text on the subject (e.g., Raiffa 1968) or a recent report to OTS that provides a more complete survey of the field (Campbell, Cohan, and North 1982, Part I). The next section considers some of the problems that arise in applying the theoretical construct to actual decisions about acquiring information. In the final section, we argue that while these problems are serious, and while decision analysis is likely to provide ambiguous answers in many instances, nonetheless decision analysis provides a useful framework for evaluating alternative information-gathering strategies.

A Simple Example

Consider a hypothetical chemical, PRC ("Potentially Regulable Chemical"), that EPA is studying for possible regulation. Analysts have developed a benefit-cost model to estimate the net benefits of banning the substance. This model includes many parameters. For the purposes of this simple illustration, however, let us assume that sufficient data are available to make accurate estimates of all but one of these parameters, the exposure level. Two exposure estimates have been made using different assumptions about the conditions under which the chemical is used. Both sets of assumptions appear to be plausible given existing information. Unfortunately, they lead to different conclusions about whether the ban would be justified. If the "high" estimate is correct, banning the substance would yield net benefits of $15 million (relative to

the status quo of "No Ban"). If the low exposure estimate is correct, however, the ban would have negligible health benefits, and the net loss would be $10 million.[3] In this example, to facilitate comparison of the ongoing costs and benefits of regulation with the one-time costs of information acquisition, assume that all dollar amounts have been discounted back to the present.

Suppose that EPA must decide "Now" whether or not to impose the ban. Figure 1 presents the relevant decision tree. We follow the usual convention that square boxes represent "decision nodes," points at which the decision maker controls which branch is selected, and circles represent "chance nodes," where the branch is uncertain and beyond the control of the decision maker. In this simple tree, we have only one node of each type: the decision node offers a choice between "Ban" and "No Ban," while the chance node has two possible branches, where the probability of high exposure is p and the probability of low exposure is 1-p

If the "No Ban" branch is chosen, the net benefits will be zero with certainty. If EPA adopts the "Ban" strategy, the net benefits will be either +$15 million or -$10 million, depending on whether exposure is "high" or "low." To find the expected net benefits of "Ban," we "average out" the uncertain branches, multiplying each of the possible outcomes by its associated probability and then taking the sum:

$$E(N) = p(15) + (1-p)(-10) \qquad (1)$$
$$= 25p - 10 .$$

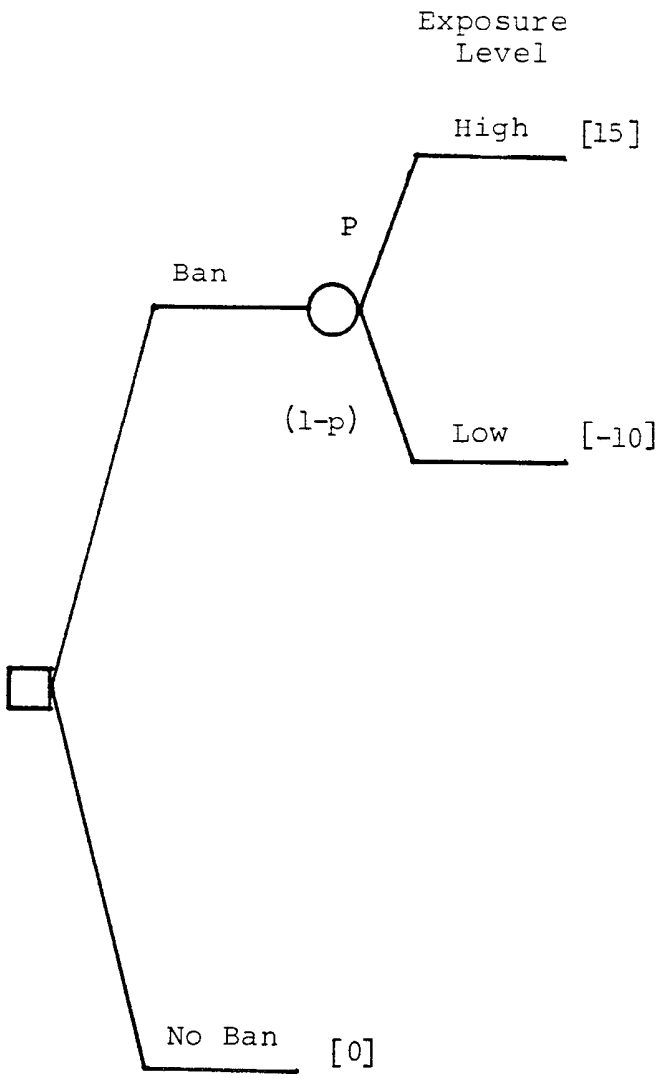

Figure 1. A Simple Example without Information

Thus, the ban yields positive expected net benefits if $p > 0.4$. To keep the example simple, let us suppose that EPA officials consider both estimates to be equally likely, so that $p = 0.5$ and the ban yields net benefits of:

$$E(N) = 0.5(15) + 0.5(-10) = +2.5 . \quad (2)$$

If the Agency follows the usual decision rule of maximizing expected net benefits, "Ban" is the best decision.

Perfect Information. Before proposing the ban, however, EPA could gather additional information to reduce uncertainty about exposure. Detailed monitoring studies might be conducted, for example, or site-specific data might be gathered to increase the accuracy of the dispersion modelling. Although in practice such studies would not eliminate all uncertainty, for now we shall suppose that it is possible to get "perfect information." That is, after the information has been acquired, the Agency will know with certainty whether exposure is high or low. Figure 2 presents the expanded tree. The initial decision is now between "Act Now" and "Gather Information." The first branch simply leads to the same tree as in Figure 1. Thus, we already know that its expected net benefit is 2.5 (because, with p=0.5, "Ban" is the best decision if action is taken on the basis of existing information).

If EPA chooses to gather information, uncertainty about exposure is resolved before the decision is made whether or not to ban the substance. In this simple example, the optimal contingent decisions are obvious: ban if exposure is high, do

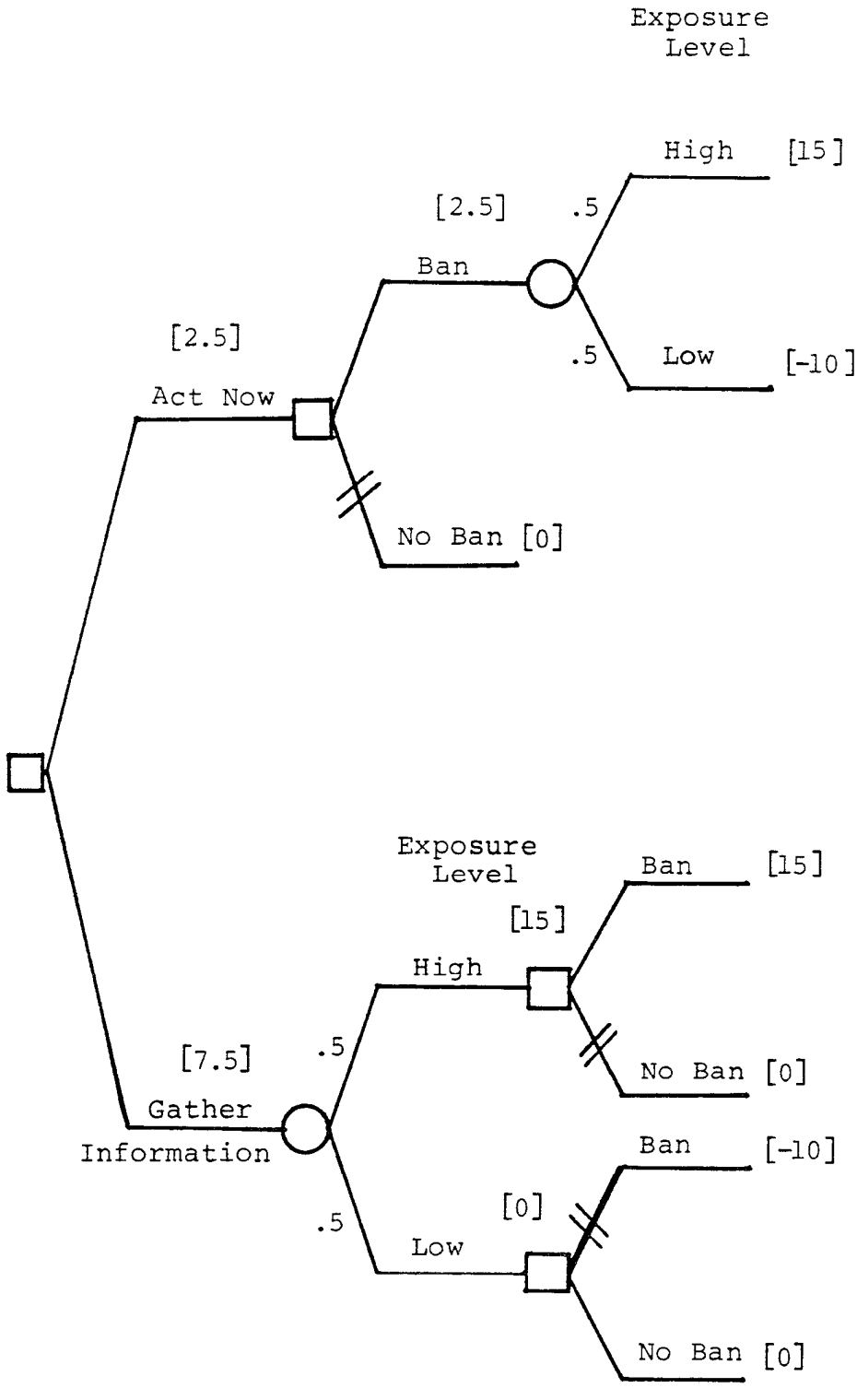

Figure 2. A Simple Example with Perfect Information

not if it is low. Thus, net benefits will be $15 million if the studies indicate high exposure, and 0 if they show that exposure is low. As both results are equally likely, the expected net benefit with information is:

$$E(N_I) = 0.5(15) + 0.5(0) \qquad (3)$$
$$= 7.5 \ .$$

The expected value of perfect information (EVPI) is simply the difference between the values of the two branches, EVPI = 7.5 - 2.5 = $5 million. Thus, the information is worth gathering if its cost (including any costs due to delaying regulation) is less than $5 million.

The EVPI also maybe calculated by noting that, ex post, the information has value only if it leads to a different decision. In this case, that occurs only if the information reveals that exposure is low. If exposure is low, net benefits are increased by $10 million (from -$10 million to 0) if the ban is not imposed. From an ex ante perspective, the value of the information is the probability that the decision will change times the change in net benefits, which is simply 0.5(10) = $5 million, as computed above.

With this second method of calculating the EVPI, we can examine very easily and intuitively the effect of changing some of the parameters of the problem. Suppose, for example, that the net loss from a ban with low exposure was only $5 million instead of $10 million. The EVPI would then fall to 0.5(5) = $2.5 million, because the consequences of an incorrect decision to ban would be lower. In the limit, if banning yielded non-negative

net benefits even if exposure was low, the information would have no value at all, because the optimal decision would be independent of the information. This limiting case suggests a more general principle, one that is obvious in a decision analytic context but that frequently is ignored in practice: information that merely refines the estimate of some quantity or relationship, but which has no chance of altering decisions, has no value.

Now suppose that we were more confident to begin with that the high exposure estimate was correct. Specifically, $p = 0.8$. In that case, the probability that the information would change the decision to ban would fall to 0.2, and the EVPI would decline to $0.2(10) = \$2$ million. Conversely, if we were less confident that the high exposure was correct, the expected value of the information would rise; if $p = 0.4$, the EVPI would rise to $0.6(10) = \$6$ million. (For $p < 0.4$, the optimal decision in the absense of the studies is not to ban, and the value of information falls as p decreases.)

Imperfect Information. Thus far we have considered only the value of collecting perfect information -- information that eliminates all of the uncertainty. More typically, however, information narrows our uncertainty but does not eliminate it altogether. (Indeed, if the imperfect information is strongly at odds with our prior beliefs, it may increase our uncertainty.) Suppose that our hypothetical exposure studies are accurate only 80 percent of the time. That is, even if the studies indicate that exposure is "high," there is still a 0.2 probability that

exposure actually is low. Conversely, if the studies indicate exposure is "low," there is a 0.2 chance that it is in fact high. Figure 3 shows how this imperfect information can be represented in the decision tree; even after the information has been obtained and a decision made whether or not to regulate, there is still a chance node between high and low exposure. The imperfect information has no effect on the "Act Now" branch; the best decision if information is not gathered is still to ban the substance, and its expected net benefit is $2.5 million. The expected net benefit of the "Gather Information" branch, however, falls to $5 million, so the information is not worth gathering unless its cost is less than 5 - 2.5 = $2.5 million. Imperfections in the information lower its value for two reasons: (1) it may lead us to change our decision when we should not have (i.e., when the studies falsely indicate low exposure) and (2) it may not alert us to the need to change the decision (i.e., when the studies falsely indicate high exposure). Note, however, that imperfect information still has value, albeit less than that of perfect information.

As these simple examples suggest, decision analysis provides a well-defined conceptual framework for calculating the value of information. Simply put, the expected value of information is the difference between expected net benefits with and without the information. Qualitatively, we can summarize the value of information in terms of three questions. First, how likely is it that the information will change the decision that would be made in its absense? The higher the probability that it will lead to

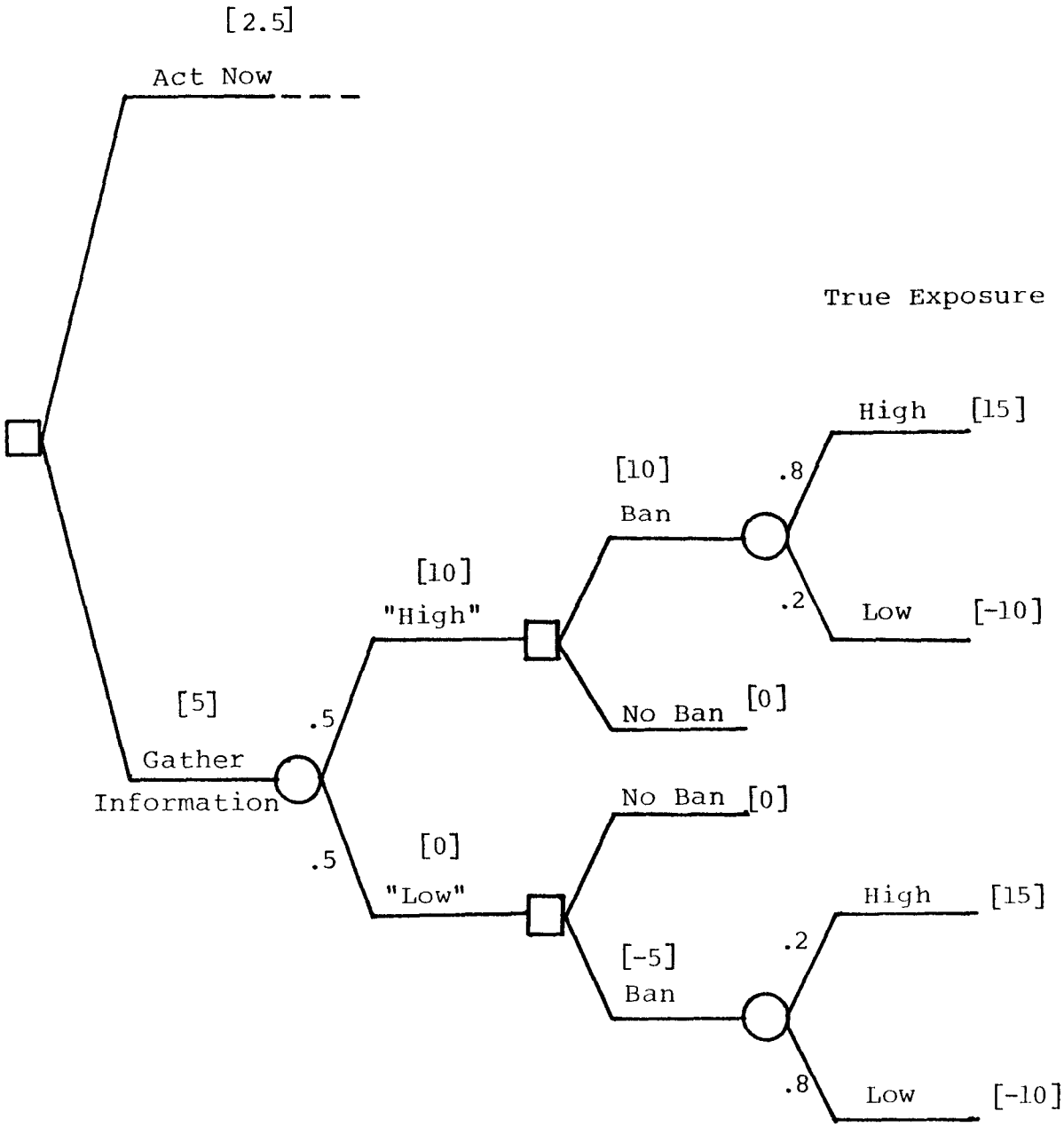

Figure 3. A Simple Example with Imperfect Information

a different decision, the higher its value is likely to be. Second, how large are the consequences of the incorrect decision that could be avoided with the information? The larger the gain is from changing the decision, the greater the value of information. Third, how accurate is the information likely to be? The expected value of perfect information provides an upper bound for the value of information.

Potential Problems In Applying Decision Analysis

The simple examples presented above sketch out the basic mechanics of applying decision analysis. The application of decision analysis to real-world problems, however, is far more complex than such examples (and others typically offered in introductions to the technique) might suggest. Although it provides a useful structure for thinking about complex, uncertain problems, decision analysis is in no sense a "cookbook" that can be implemented in a mechanical, purely technical manner. Careful judgment is required at each stage, from the initial formulation of the problem in decision-tree form, through the estimation of parameter values on the basis of sketchy and conflicting information, to the interpretation of the results. In this section, we consider some of the obstacles that confront efforts to use decision analysis to estimate the value of information relevant to regulating suspect toxic chemicals.

Structuring the Tree. In our simple example, EPA had a very limited number of decisions to make: its ultimate choice was between "Ban" and "No Ban." Its only other choice was whether to

make that decision immediately or to wait until it had gathered more information on exposure. In practice, however, the Agency is likely to have many more choices. Regulation can take many different forms, including labeling requirements, emission limits, or a ban on some or all uses. Within each type of regulation, there are many gradations; emission limits, for example, can be set at many different levels. Each of these alternative decisions becomes a branch on the tree and, more importantly, the base from which other branches spring.

Our example also was too simple in that it included only one source of uncertainty, the exposure level. In practice many parameters are likely to be highly uncertain, particularly during the early stages of evaluating a substance for regulation. Data on control costs, for example, may be minimal or nonexistent. Plausible estimates of the risk posed by exposure almost certainly will vary by orders of magnitude. The Agency may not even be able to get reliable data on how much of the substance is produced, which will affect its estimates of both the costs and the benefits of alternatives. Incorporating these uncertainties quickly enlarges the tree. With three sources of uncertainty and only two possible values for each, there are $2^3 = 8$ possibilities. With 5 sources and 4 possible values for each, there are $4^5 = 1024$ "tips" that need to be evaluated.

Multiple uncertainties also raise the possibility of gathering additional information on a wide variety of parameter values. In our example, EPA had to decide whether or not to refine its estimate of exposure; typically it might also have the option of gathering information on several other uncertain

quantities. The structure of the tree quickly becomes even more complicated because information-gathering activities can be sequenced in different ways. Suppose, for example, that EPA could get information on costs as well as exposure. Which, if either, should it gather first? After it gathers one, should it stop, regulate, or gather the other type of information as well? (The right choice, of course, is likely to be dependent on the results of the first round of information acquisition.) The Agency also may wish to consider gathering both types of information simultaneously to avoid excessive delay before a final decision is made.

As these examples suggest, consideration of even a significant fraction of the possibilities can quickly turn a tree into what Raiffa (1968) calls a "bushy mess." The problem with highly complex trees is not primarily computational; even very large trees can be evaluated fairly quickly with the aid of the computer. The more important problem is that as the number of branches grows, so too does the number of probabilities that must be estimated. Moreover, as the structure of the tree becomes more complicated, it may become impossible for anyone other than those intimately involved in its development to understand it, thus severely limiting its usefulness as a vehicle for communication. Decision makers are likely to be reluctant, and rightfully so, to rely on a model that they cannot understand, particularly when so many of its components are based on subjective judgements.

Assessments of Probabilities. Once the basic tree has been structured, the problem is to assess the probabilities associated with the various branches. In our example, we merely asserted that EPA considered the two alternative exposure estimates to be "equally likely," and thus assigned a probability of 0.5 to each. In practice, however, such probabilities are extremely difficult to assess. In some cases, there may be reliable data available for at least some of the components; we may, for example, have good data on the distribution of chemical plants by population density. More often, however, particularly in dealing with hazardous chemicals, there is no way to develop an estimate that can be defended as rigorous or objective. Scientists, for example, hold widely varying opinions about the appropriate methods for estimating low-exposure risks from high-exposure animal studies. It is easy to generate alternative risk estimates that vary by orders of magnitude. The difficulty lies in assessing what probabilities should be attached to those estimates. Various techniques have been developed for eliciting probabilistic judgements from experts, but they are often difficult to use and are likely to be too time consuming and expensive to use except for a few key parameters in analyses of major decisions. In many cases, the analyst may have to rely on rough, subjective estimates made by a single individual (often himself).

Probability estimates become especially critical, and difficult to make, when estimating the value of information. In our example above, for instance, if the only choices are "Ban" or

"No Ban," the former is optimal so long as the probability of "high" exposure (p) is greater than 0.4. The value of perfect information is more sensitive, however, to the estimate of p, ranging from $6 million for p=0.4 to $3 million for p=0.7 and $0 for p=1.0.

Imperfect information complicates the problem still further, because it requires that the analyst estimate not only the prior distribution on the true parameter value, but also what the distribution will be conditional on different information. In our example of the value of imperfect information, we assumed that the information would be correct 80 percent of the time. That type of estimate, however, is extremely difficult to make in most cases because the errors in the information are hard to quantify. Rarely does information take the form of a "test" for which we have reliable, historical data on the probabilities of false positives and negatives. In the next chapter, for example, we discuss the problems that may arise with a Section 8(a) rule because some firms fail to report (either because they are not aware of the rule or they simply choose not to bother) and other firms may report inaccurate information (either inadvertantly or intentionally). Although it is possible to identify the potential sources of inaccuracy, it is impossible to estimate their quantitative significance with any confidence. One commmonly used alternative is to estimate the EVPI, thus obtaining an upper bound on the value of the imperfect information that actually will be obtained; if the information costs more than that upper bound, clearly it is not worth gathering. If the cost is less than that upper bound, however,

the appropriate decision is unclear, because the value of imperfect information may be much lower than the EVPI suggests.

Deciding What Information Can Be Collected. The more general problem is to determine what information can be collected or, if a specific proposal has been made, what information it will provide. Once the basic decision tree has been set up and the parameters estimated, it is relatively easy to estimate the value of refining certain parameter values. Such estimates can be useful in thinking about what kinds of information are most important. To be relevant, however, the estimates must be made for information that could be obtained at less than astronomical cost. It does little good to demonstrate that it would be extremely valuable to refine some parameter value if there is no feasible way to obtain the information necessary.

Campbell, Cohan, and North's (1982) otherwise excellent case study of perchloroethylene (PCE), a suspected carcinogen, provides a clear example of this problem. They employ a decision-analytic framework to evaluate regulatory alternatives for PCE used in dry cleaning plants. Many of the parameter values are uncertain. As with most toxic substances, however, uncertainty about the risk factor dominates all other sources of uncertainty in the analysis. Campbell, Cohan, and North identify three critical subissues in estimating the risk factor from high-dose experiments with laboratory animals: (1) Should the extrapolation be based on the studies with rats or mice? (The mouse study showed a much higher incidence.) (2) In extrapolating from high to low doses, should the model be linear

or nonlinear? (The linear model gives much higher estimates than the alternative they considered, a quadratic.) (3) Should the extrapolation from animal to man be based on relative weights or surface areas? (The surface area conversion gives a higher risk estimate.) Their discussion of these issues is commendable for its emphasis on the importance of considering the range of alternatives rather than a single, "worst case," as is done so often.

Campbell, Cohan, and North then consider the value of obtaining perfect information on each of these uncertainties, both singly and in combination. They conclude that such information, particularly on the correct dose-response model, would be extremely valuable. The analysis is carefully done and clearly presented, in many ways a model for such efforts. Unfortunately, it is also of little relevance, for there is no apparent way to reduce these uncertainties significantly, let alone perfectly. All of these issues have been debated by scientists for many years, with respected champions for each position, and no resolution is in sight. In contrast, Campbell et al. devote no attention to the many other uncertainties in the problem that, while less critical, potentially could be reduced at reasonable cost. The exposure data, for example, show wide variability, and presumably the estimates could be improved with more monitoring.

Multiple Uses For Information. The PCE study also illustrates another potential problem in estimating the value of information: information collected for one purpose may affect

other decisions as well, decisions that are not included in the formal analysis. The uncertainties considered by Campbell, Cohan, and North, for example, are generic ones that arise in regulatory decisions about many substances, not just PCE. Resolving them would have enormous benefits well beyond those estimated for PCE alone. If, for example, it could be shown that the correct model for extrapolating from high to low doses is quadratic, so that low-dose risks are negligible, we could abandon most efforts to regulate environmental carcinogens, thus saving large sums of money every year. In contrast, if the linear model were shown to be correct, much of the controversy and litigation that now surrounds such regulation would disappear, allowing EPA to proceed more rapidly to reduce exposures and protect public health.

For basic scientific questions of this type, which are applicable to a wide range of regulatory decisions, it makes little sense to estimate the value of information in the context of a decision analysis of a specific substance or class of sources. Such information may be thought of as a classic public good. Its value in any one decision will be only a tiny fraction of its total value. Thus, analyses of the value of basic knowledge of this type must be made in a much broader context. We doubt that formal decision analysis will be of much value in guiding such choices, because the number of decisions that would be affected by the information is so large, and it is so difficult to predict the probability of success in basic research.

More commonly it will be the case that information gathered for one decision, while not of broad applicability, will have spillover benefits for other decisions. In the language of economics, such information generates positive externalities. Cost or exposure estimates made for one chemical, for example, may be used for later decisions involving other chemicals with similar characteristics. Information gathered by OTS may be used by other offices within EPA or by other agencies, such as OSHA, the CPSC, or the FDA. The danger is that if the value of information is calculated in a framework that does not encompass these other uses, it may be underestimated significantly. Suppose, for example, that OTS was considering monitoring studies to obtain better estimates of exposure levels from solvents containing a hazardous chemical. It might well conclude that the cost of the studies was too high relative to their expected benefits in improving decisions about that particular chemical. It might also find, however, that the studies would aid in evaluating regulatory alternatives for other chemicals used in solvents, and that once those "external" benefits were considered, the studies would be justified on benefit-cost grounds.

In some cases it may be possible to account for these external benefits by extending the decision tree to incorporate other decisions that would be affected by the information. Where that extension can be made without rendering the tree hopelessly complex, clearly it is desirable. Often, however, it will not be possible. In most cases, a more modest and informal treatment probably is desirable. At a minimum, the analyst should note

other agencies or regulatory programs where the information is likely to be of value. It would also be desirable to contact the relevant agencies to get at least a qualitative estimate of the importance of the information. (Such contacts also may lead to modifications in the information gathered to make it more useful to these other decisions.) Where possible, specific decisions that would be affected by the information should be identified. Although this process would not generate data that could be included in the formal calculations, it could prove a valuable qualitative input in deciding whether or not to gather the information.

The Role of Judgment in Applying Decision Analysis

The problems described above are formidable. They should not, however, be allowed to obscure the very real advantages of using decision analysis to aid decisions about information acquisition. Those who look to decision analysis as a "decision-making machine" that will generate clear choices automatically, once supplied with a few pieces of data, inevitably will be disappointed. But that is too much to ask of any methodology. As with benefit-cost analysis and other quantitative techniques, decision analysis is better thought of as an aid to decision makers, a way of organizing thinking and information. Viewed from that more modest and realistic perspective, decision analysis has a great deal to offer.

No model can capture all of the details of complex situations. An important task in any modeling effort is to

decide the levels of detail at which different aspects of the problem will be represented in the model. This is particularly crucial in decision analysis, where multiple uncertainties and alternative decisions can quickly expand to create a tree that is overly complex and impossible to understand. Decision analysis must be viewed as an iterative process in which the structure of the tree and the parameter estimates are refined over time.

Typically the analysis starts with a very simple representation of the problem, one that strips it to its bare essentials. The initial parameter estimates also are likely to be extremely rough. Sensitivity analyses can then be performed to indicate where it is important to refine parameter estimates and to alter the structure of the tree to include more possibilities. The number of logical possibilities usually is very large, so that judgment is required to determine which can be excluded. This iterative process often leads to subtractions as well as additions; some simple calculations or additional thought may reveal that alternatives that initially looked promising are highly unlikely to be optimal. Where parameter estimates are uncertain, but the uncertainty is not crucial or it becomes clear that information cannot be obtained to update those estimates, it may be desirable to eliminate some chance nodes, substituting expected values.

This iterative process also can proceed in "real time," as decisions are made and new information becomes available. Early in the process of evaluating some chemical for regulation, for example, the key issue may be whether or not it is toxic. The decision tree used to decide whether to order testing is likely

to focus on alternative types of tests and their relative costs and accuracies. It probably will not include much detail on regulatory options, which will not be chosen until many other decisions have been made and a great deal of additional information has been acquired. At later stages in the regulatory process, however, when specific regulatory alternatives must be chosen, that part of the tree can be elaborated, with more details added.

As this discussion suggests, we believe that decision analysis is most useful when used as an integral, ongoing part of the decision-making process, rather than as a "test" that is brought in to determine if a particular decision or information request is "justified." The decision-analytic framework provides a valuable discipline for decision makers, in part because it forces them to make tentative estimates of costs and benefits earlier than they otherwise might. It also forces them to articulate more clearly, at least in their own minds, what they hope to get from information. The most basic principle of decision analysis, that information is valuable only if it might lead to different decisions, often is ignored or forgotten. Colleagues of ours who have applied decision analysis to medical decisions, for example, report that physicians who are not familiar with decision-analytic principles often order tests even when the results will have no impact on the course of treatment.

Merely asking the question -- "How will I behave differently once I get this information?" -- can have a beneficial impact by reducing the resources devoted to acquiring unproductive information.

The application of decision analysis to complex problems clearly involves as much art and judgment as science. In principle, decision analysis offers the most promising framework for evaluating the benefits of acquiring information on toxic substances, whether under Section 8(a) of TSCA or by other means. To move beyond the level of vague generalizations, however, we need to examine the usefulness of decision analysis in the context of a specific, real problem.

IV. AN OVERVIEW OF THE EDC CASE STUDY

Ethylene dichloride (EDC) is a high-volume industrial chemical, used primarily as a feedstock to produce vinyl chloride monomer (VCM) and other industrial chemicals. In 1978, the National Cancer Institute (NCI) released the results of life-time studies of laboratory animals exposed to EDC; both rats and mice showed an increased incidence of cancer. Since that time, the Consumer Product Safety Commission (CPSC), the Food and Drug Administration (FDA), the Occupational Safety and Health Administration (OSHA), and several program offices within EPA have studied EDC for possible regulatory action, though none as yet has proposed new regulations.

Of the 5.2 billion kilograms of EDC manufactured in 1979, approximately 85 percent was used to manufacture VCM, and another 10 percent was used as a feedstock in other production processes. Roughly 3.4 percent was exported, and about 1.6 percent was used as an additive in leaded gasoline. It is estimated that less than 0.1 percent of total EDC production was employed in "dispersive" uses other than gasoline. Although dispersive uses account for only a tiny fraction of total EDC consumption, they may cause as much as one-third of all emissions, because virtually all of the EDC in such uses is released to the environment, while emission rates for EDC production facilities and plants using it as a feedstock are very low (Seufert et al.

1980). Thus, it appears that dispersive uses account for a disproportionate share of the potential risk from EDC and may offer cost-effective candidates for regulation.

In its efforts to estimate the risks posed by dispersive uses of EDC and to formulate regulatory options, EPA has been hampered by very limited information about the particular uses to which EDC is put and about the actual volumes involved. These uncertainties make it exceedingly difficult to estimate the costs and benefits of alternative regulatory strategies, or indeed even to know to what products or production processes regulations might apply. Efforts by consultants to obtain information from published sources, existing data banks, manufacturers of EDC, trade associations, and various experts have yielded results of dubious accuracy. In 1981, EPA drafted (but never formally proposed) a rule under Section 8(a) of TSCA that would have required processors to report information on EDC sold (either by itself or as part of a mixture for dispersive uses: the rule would not have applied to EDC sold as a feedstock, used as a fuel additive, or incorporated in a registered pesticide. Officials in EPA's Office of Toxic Substances suggested this particular draft rule for a case study of the value of information that could be acquired under Section 8(a).

To estimate the value of the information that would be provided, we need to assess how that information might affect decisions and net benefits. This chapter lays out the information currently available on dispersive uses of EDC, including estimates of volumes and types of use, exposure levels, risk estimates, and control costs. In Chapter 5 we develop a

decision analytic framework to use that information to estimate the value of the information that would be obtained under the proposed rule.

Volumes and Uses of EDC

Table 1 presents the volumes of EDC employed in various uses in 1979, as estimated by an EPA contractor (Seufert et al. 1980). The uses are grouped into four categories: feedstocks, which dominate with 95 percent of the total; exports; gasoline and pesticides; and "other" dispersive uses. The first three categories are not relevant to the proposed rule, but are presented to put the volume of uses covered by the rule in perspective. The first two categories are not "dispersive;" the uses in the third, while dispersive, would not be covered because firms already must report under other laws. (Refiners must report fuel additives under the Clean Air Act, and pesticide manufacturers must report their ingredients under FIFRA.) As noted earlier, dispersive uses that would be covered by the rule appear to account for less than 0.1 percent of total production. The estimate for this category is extremely uncertain, however, and, for reasons discussed below, probably is too high.

Consultant Studies. At least eight studies by consultants to various EPA program offices contain information on dispersive uses of EDC. The sheer number of reports is misleading, however, because with one exception these reports rely on a single study by Auerbach Associates (Mazella 1978) for their estimates of dispersive volumes. That study, in turn, provides no source for

Table 1. Estimated Volumes of EDC by Use

Use	Volume(1000 kg)	Percent of Total
Feedstocks		
Trichloroethylene	89,400	1.7
Perchloroethylene	137,800	2.7
Vinylidene Chloride	118,700	2.3
Ethylene Amines	168,000	3.2
Polysulfides	523	.01
VCM	4,420,000	85.0
Subtotal	4,934,423	94.9
Exports	179,000	3.4
Gasoline and Pesticides		
Lead Scavenging	81,700	1.6
Grain Fumigants	460	0.01
Subtotal	82,160	1.6
Other Dispersive Uses		
PVC Reactor cleaning and Textiles	910	0.02
Paints, Coatings, and Adhesives	1364	0.03
Extraction Solvents	1050	0.02
Miscellaneous Uses	460	0.01
Subtotal	3784	0.07
Grand Total	5,200,000	100.0

Source: Seufert et al. (1980)

its estimates of the dispersive uses covered by the draft 8(a) rule other than a "personal communication" from another consulting firm. The figures in Table 1 for dispersive uses, though nominally from GCA, are simply the Auerbach estimates converted from pounds to kilograms. All of the original estimates included only a single significant digit; the estimate for "paints, coatings and adhesives," for example, was 3 million pounds.

A more recent study by SRI International (Gibson et al. 1981) estimated substantially lower quantities. Table 2 compares the two sets of estimates. While Auerbach estimated a total of 8-9 million lbs in dispersive uses covered by the potential rule, the SRI total was only 3.75-4.75 million lbs. Moreover, in several categories SRI denoted its figures as upperbound estimates. Several explanations may be offered for the difference between the two estimates. One is that dispersive uses of EDC are declining; the Auerbach estimate is for 1977, while the SRI estimate is for 1979, though given the crude and impressionistic nature of both estimates it is difficult to associate either with a particular year. Some of the SRI figures, for example, are based on data from an occupational survey conducted in 1972-74. Another plausible explanation for the apparent differences is that they reflect errors in one or both of the estimates rather than any underlying real time trend.

Table 2. Comparison of Dispersive Volume Estimates for 1977 and 1979

Auerbach Estimate (for 1977)		SRI Estimate (for 1979)	
Use	Volume (million lbs)	Use	Volume (million lbs)
PVC and textiles cleaning	2	PVC cleaning	1-2
Paints and adhesives	3	Paints and removers	<0.5
		Adhesives	<0.25
Extraction solvent	2-3	Pharmaceuticals	1
		Food applications	<0.5
Other	1	Miscellaneous	0.5
Total	8-9	Total	<3.75-4.75

Sources: "Auerbach" estimate from Mazella (1978)

"SRI" estimate from Gibson et al. (1981)

Evidence is available to support both hypotheses. SRI notes that one major difficulty in obtaining information on dispersive uses is that the market for such uses is so small that producers of EDC have not bothered to keep track of them for marketing purposes. Moreover, it appears that

> many of the scattered small volume consumers are supplied by distributors, resellers, or jobbers who ship EDC in 5-gallon pails or 55-gallon drums. These distributors market broad lines of chemical products and generally have little or no idea of an individual customer's application for EDC (Gibson et al. 1981, p.3).

Although the SRI estimates are highly uncertain, they appear to have been done with substantially more care than those by Auerbach. Thus, to the extent that the differences between the two estimates are due to errors, we would place substantially greater faith in the SRI figures.

There is also evidence that the differences between the two estimates reflect real declines in dispersive uses of EDC. The Auerbach estimate was made for a period prior to the release of the NCI bioassay results showing that EDC is an animal carcinogen. Apparently some manufacturers eliminated EDC from their products after learning of its carcinogenicity. A study for the CPSC, for example, found that EDC had been eliminated from two adhesives and was unable to find any consumer products that used EDC after the NCI report. The FDA in 1978 also was unable to find any registered pharmeceuticals or cosmetics that incorporated EDC, although it still may be used as an extraction solvent for certain foods and pharmaceuticals (Gibson et al. 1981). A discussion of individual use categories follows.

Paints, Coatings and Adhesives. EDC has been used in a few paints and coatings, apparently as a carrier solvent in fast-drying formulations. It has also been used in some paint strippers, though it is only 45 percent as effective as methylene chloride, the major active ingredient in most strippers. Effectively all of the EDC in paints and strippers evaporates upon use.

The amount of EDC used in these applications appears to be minimal and declining. SRI reports that manufacturers of EDC knew of no current uses in paints or strippers (Gibson et al. 1981). GCA reports that none of the three major paint manufacturers contacted used EDC in its products, though they believed it was used in some industrial products (Seufert et al. 1980). In a search of NIOSH's Tradename Ingredient data file, SRI was able to find only two paints containing EDC, both manufactured by the same company and both containing 6 percent EDC (Gibson et al. 1981). A search of the NIH-EPA Chemical Information System CTCP data base yielded a single paint remover containing 10 percent EDC. It is not clear that even these products still contain EDC, however. With regard to paint removers, SRI reports that "industry sources believe that few current formulations contain EDC and that it will rapidly disappear as an ingredient in this application" (Gibson et al. 1981, p.22).

The use of EDC in adhesives also appears to be declining. NIOSH lists several adhesives containing EDC, but that list was based on the 1972-74 National Occupational Hazard Survey (Gibson et al. 1981). In 1979, a CPSC survey of EDC in consumer products

found that manufacturers of consumer products had switched to alternative solvents; it identified seven specific products that formerly had contained 10-20 percent EDC (Gibson et al. 1981). SRI further reports that "there was no indication from producers or distributors of EDC that the chemical is currently being used in any adhesives." It is possible, however, that some industrial adhesives still contain EDC, though no specific products have been identified.

This qualitative evidence appears to be consistent with SRI's conclusion that no more than 0.5 million lbs of EDC were used in paints and coatings in 1979, and that adhesive uses of EDC in that same year were under 0.25 million lbs. Moreover, it appears likely that the use of EDC in both areas has declined since 1979, as manufacturers have had more time to become aware of the NCI results and to reformulate their products.

Extraction Solvents. EDC has been used as an extractant for a variety of purposes in food processing and the manufacture of pharmaceuticals. Use has been declining, however, and it is likely that few applications remain. SRI quotes "industry sources" as reporting that EDC is no longer used to extract animal fats or oils from seeds. It may have been used in the past to extract caffeine from coffee, but is no longer. A 1977 survey by the National Academy of Sciences reported the use of 470,000 lbs of EDC in food applications, but that total may have included fumigants (which are not covered by the proposed Section 8(a) rule) as well as extraction solvents and cleaning solvents for machinery (National Research Council 1979, as reported in

Gibson et al. 1981). The reader should also note that the NAS survey was conducted prior to release of the NCI studies. Thus, it appears likely that the use of EDC as an extractant for foods was well below the SRI upper-bound estimate of 0.5 million lbs in 1979.

SRI reports that producers and resellers continue to market EDC for use in the pharmaceutical industry as a reaction intermediate (which would not be covered by the 8(a) rule as drafted) or as a processing or purification solvent. It is important to note that SRI's estimate of 1 million lbs is for net consumption of EDC; SRI reports that "consumers attempt to recycle and repurify the solvent" and that "solvent loss is minimized" (Gibson et al. 1981, p. 10). These statements suggest that controls already are quite tight for economic reasons, and that additional controls might be relatively expensive at the margin.

PVC Reactor Cleaning. EDC is used as a solvent to clean the scale buildup from the walls of reactor vessels used to produce PVC. Several other chlorinated solvents are also in use, and presumably could be substituted in those plants currently using EDC. Several factors make it difficult to estimate the net amount of EDC consumed for reactor cleaning. The primary problem is that PVC and VCM often are produced in integrated plants, so that the EDC used to clean reactors is simply siphoned off from feedstock storage tanks. After heated EDC has been used to dissolve PVC on the reactor walls, the solution is transferred to another tank where the EDC is stripped away and recycled. The

frequency with which the reactors must be cleaned varies widely across plants, from every 2-10 batches in older plants to once every several hundred batches in some newer plants (Seufert et al. 1980). Presumably the efficiency of the recovery and recycling process also varies widely across plants. As SRI notes, the estimated consumption of 1 to 2 million lbs of EDC for reactor cleaning is minuscule compared to the roughly 12 billion lbs used to produce VCM and eventually PVC (Gibson et al. 1981). In light of these facts, it seems unlikely that the draft 8(a) rule would provide much information on the amount of EDC consumed in reactor cleaning; it is not even clear that "processors" would have to report its use, as EDC probably never is packaged specifically for this application.

Miscellaneous Uses. A large number of potential low-volume uses has been identified in consultant reports. These include milk preservation, cleaners and grease removers, copper ore leaching, and photographic film cleaning. It is difficult to tell, however, how many of these uses currently are active, or indeed were ever significant consumers of EDC. The consultant reports typically refer to industry sources who have heard of possible uses, but whose own companies do not use EDC, or to older publications that list potential uses. SRI reports that the NIOSH Tradename Ingredient data base lists about a dozen miscellaneous products as containing EDC, but as noted earlier that list is based on a 1972-74 survey (Gibson et al. 1981). In at least some of the potential applications, such as copper ore leaching, it appears that the EDC would be chemically transformed

rather than released (Slimak et al. 1980). Given the paucity of information, it is difficult to evaluate the accuracy of the SRI estimate for 1979 of 0.5 million lbs of EDC in miscellaneous uses. We note, however, that the few specific pieces of information post-1978 appear to be negative; EDC is listed as a possible ingredient of nail polishes and removers, for example, but in 1978 the FDA concluded that it was no longer used in any cosmetics.

Emissions

Almost by definition, dispersive uses of EDC have high emission rates. In many uses, such as paints and adhesives, it appears likely that all of the EDC is released to the air as the material dries. In other uses, such as PVC reactor cleaning and pharmaceuticals extraction, much of the EDC is captured and reused; in those cases, however, the estimates of the volumes used refer to net consumption, the amounts of EDC that are "lost" annually and need to be replaced. In a few potential dispersive uses (e.g., copper ore leaching), most of the EDC may be converted to other substances, so that emission rates are very low. In general, however, it appears reasonable to assume that all of the EDC employed in dispersive uses is emitted, recognizing that in some categories our estimates of "use" more accurately could be characterized as estimates of emissions.

Exposure to EDC

Exposure per unit of EDC emitted will vary widely depending on the type of use and its location. EDC used as an extractant for pharmaceuticals in a well-ventilated, capital-intensive factory in a lightly populated area, for example, is likely to cause little exposure for either workers or the general public. In contrast, an EDC-based adhesive used in a poorly ventilated urban repair shop may result in very high exposures for a few workers and relatively high exposures for large numbers of nearby residents. To estimate overall exposures accurately, we would need estimates of both exposure factors for individual dispersive uses and estimates of the distribution of EDC across those uses. Unfortunately, neither set of estimates exists. Indeed, one of the potential benefits of the proposed Section 8(a) rule is that by providing better information on uses it would facilitate the gathering of exposure data.

Human exposure to dispersive uses of EDC may be broken down into three categories: occupational exposure, exposure to users of products that contain EDC, and general population exposure due to emissions to the atmosphere. Because of uncertainty about the quantity of EDC employed in dispersive uses, the numbers of plants and workers who handle EDC, the products that contain EDC, the concentrations to which workers, users, and the general population might be exposed, as well as the duration of possible exposure, it is exceedingly difficult to produce an estimate of total human exposure from dispersive uses that can be defended with much confidence.

Ambient Exposures. Several dispersion models are available for use in estimating exposure factors for members of the general public exposed to EDC released into the ambient air. One such model is the Hanna-Gifford area-source dispersion model, which assumes that emissions occur uniformly over the area in question. This model was used, for example, to estimate exposures to benzene from automobiles and service stations (Mara and Lee 1978). It takes the following form:

$$C = 225Q/u \ , \qquad (4)$$

where C is the average annual concentration in ug/m^3, Q is the emission rate in grams per second per km^2, u is the average windspeed in meters per second, and 225 is an empirical constant. Using this model, the estimated exposure factor, measured in ppb-person-years/kg emitted, is:[4]

$$X = 1.74 \times 10^{-3} \ (D/u), \qquad (5)$$

where D is the population per km^2. Substituting typical urban values of D = 1318 and u = 5.5 (Mara and Lee 1978) yields an exposure factor of:

$$X = 1.74 \times 10^{-3} \ (1318/5.5) = 0.42 \text{ ppb-person-years/kg} \qquad (6)$$

This estimate probably is too high, because many sites where EDC is used dispersively are not located in urban areas, and even those that are urban are likely to be in industrial areas with lower-than-average densities.

Campbell, Cohan, and North (1982) have estimated levels of exposure to perchloroethylene (PCE) for nearby residents of dry-cleaning plants where PCE is used as a cleaning agent. They assume that such plants are located in urban areas. Although they do not calculate an exposure factor, it is possible to use their data to estimate one of 0.25 ug/m^3-person-years/kg, or 0.06 ppb-person-years/kg. Part of the explanation for the difference between this estimate and the one above is that Campbell, Cohan, and North did not account for exposures to people living more than 1 km away from the plants.

Estimated exposure factors for benzene emitted from individual maleic anhydride plants, based on generalized dispersion modeling but plant-specific population data, range from 0.008 to 0.391 ppb-person-years/kg, with a mean value of 0.2 (Nichols 1983). Multiplying by (3.2/4.1) to take account of the difference between benzene and EDC in converting ppb concentrations into ug/m^3, that implies a range of 0.006 to 0.305, with a mean exposure factor of 0.16 ppb-person-years/kg for EDC. Those estimates assume, however, that the substance is emitted from a stack, which probably is not the case for most dispersive uses of EDC.

Dispersion modeling performed for coke oven emissions and for four types of plants emitting acrylonitrile provide other ranges of values that may be useful in making rough estimates of exposure factors for EDC. As with the estimates for maleic anhydride plants, these estimates were made using a generalized dispersion model and plant-specific population figures. Exposure factors, measured in ug/m^3-person-years per kg emitted, ranged

from 0.058 to 5.93 for coke ovens, with a mean of 2.8. Converted to ppb-person-years/kg, the range is 0.014 to 1.80, with a mean figure of 0.69. For plants emitting acrylonitrile, the range of exposure factors was 0.009 to 1.14 ug/m^3-person-years/kg, with a mean of 0.146 (Haigh, Harrison and Nichols 1983); those estimates translate to a range of 0.002 to 0.28, with a mean of 0.36, when measured in ppb-person-years/kg.

Little faith can be placed in any one of these estimates. Taken together, however, they suggest that the average non-occupational exposure caused by dispersive uses of EDC probably is lower than 0.5 ppb-person-years/kg.

Occupational Exposure. Virtually no data exist on which to base an estimate of occupational exposures to dispersive uses of EDC. NIOSH has estimated that as many as 150,000 worksites may use EDC and that as many as 2 million workers may be exposed (NIOSH 1978, as reported in Perwak et al. 1981). Both figures are likely to be substantial overestimates, particularly the latter as it includes all workers at sites that may use EDC, not just those workers who actually work in parts of the sites where EDC is used. Moreover, the estimate was made prior to the release of the NCI bioassay results, which apparently has led to some reduction in EDC use. Finally, the NIOSH estimates include all uses of EDC, not just the dispersive uses of interest here, and they also fail to include any information on exposure levels.

(The current OSHA limit is 50 ppm, but it is unlikely that many workers are exposed to concentrations even approaching that level for any appreciable portion of the working day.) Thus, for our purposes the NIOSH estimates are of virtually no value.

In their study of PCE, Campbell, Cohan, and North (1982) also estimated occupational exposures, based on actual monitoring of workers in several dry cleaning plants. Their estimates imply an exposure factor of about 14 ug/m^3-person-years/kg of PCE, which would translate to 3.4 ppb-person-years/kg of EDC. Several factors suggest, however, that this figure is too high to use as an average estimate for an EDC exposure factor. First, we suspect that dry cleaning plants are substantially more labor-intensive than many workplaces where EDC is used (e.g., PVC and pharmaceutical plants), in particular because Campbell et al.'s estimates included industrial laundry workers who are unlikely to work in the parts of dry-cleaning/laundry plants where PCE is used. The nature of the dry-cleaning process also is likely to lead to relatively high exposure levels; in most plants, the machine operator transfers solvent-soaked clothing from a cleaning machine to a drying machine, thus coming in very close contact with PCE.

Although we believe that occupational exposure factors for EDC are likely to be lower than might be inferred from Campbell, Cohan, and North's implicit estimate for PCE, their results do suggest that failing to account for occupational exposures could lead to a substantial underestimate of the potential benefits of

regulating EDC. It also may suggest, however, that dispersive uses of EDC are a regulatory issue of greater relevance to OSHA than to EPA.

Consumer Exposure. We are not aware of any attempts to estimate exposure levels for consumers using products that contain EDC. As discussed earlier, however, it appears that the use of EDC in consumer products, which was never high, probably is now virtually nonexistent, so that we feel comfortable in assuming that consumer exposure to EDC is negligible.

Risk from Exposure to EDC

The primary health effect of concern for exposure to EDC is cancer, although some occupational exposures possibly may be high enough to cause other ill effects. The major sources of evidence, and virtually the only bases on which to do quantitative risk assessments, are the NCI studies of rats and mice that were mentioned earlier. In those studies, the animals were given high daily doses of EDC by gavage (i.e., through a tube to the stomach). Several types of cancers and benign tumors were observed, with the specific types and incidences varying with species and sex. In contrast, Maltoni et al. found no increased incidence of cancer in rats and mice exposed by inhalation to EDC at concentrations up to 600 ppm (Maltoni et al. 1980, as reported in Perwak et al. 1981).

The uncertainties associated with extrapolating from high-dose animal experiments to low-dose human exposures are well known, though largely unquantified. The major uncertainty is the

appropriate dose-response model for extrapolating from high to low doses. The most widely used model is the "one-hit" or "linear" model, which predicts that at low doses risk is proportional to exposure; cutting exposure by a factor of 10 reduces risk by that same factor. A wide range of other models has been proposed; virtually all of them predict that as exposure is reduced, risk falls more rapidly. When estimated from the same high-dose data, these other models typically predict low-dose risks that are several orders of magnitude smaller than those estimated by the more conservative linear model.

The second major source of uncertainty concerns the extrapolation from animals to humans. Although most scientists accept findings of excess cancers in animal studies as strong evidence that the substance will also cause cancer in humans, there is considerable disagreement as to how to use animal data for quantitative risk assessment. The most concrete manifestation of this disagreement arises in computing equivalent doses. The most widely used method is to convert on the basis of body weight. Under this method, a dose of 5 mg per day for a .03 kg mouse would be treated as equivalent to a (70/.03)(5) = 11,667 mg daily dose for a 70 kg person. Some scientists argue, however, that equivalent doses should be computed on the basis of relative surface areas. EPA's Carcinogen Assessment Group (CAG) uses this method. As surface area rises approximately with the two-thirds power of body weight, this leads to a substantially lower estimate of the equivalent human dose, and thus a higher risk estimate. For our hypothetical example of a mouse fed 5 mg per day, the equivalent human dose by this method would be

$(5)(70/.03)^{(2/3)}$ = 880 mg, lower by more than a factor of 13. With rats, which are much larger than mice, the difference between the two conversion methods is smaller, but still roughly a factor of 6.

Several other issues contribute additional uncertainty to risk estimates. How should ingested doses be converted into equivalent concentrations in air that is inhaled? Typically it is assumed that the route by which the substance enters the body is irrelevant (e.g., breathing 10 m^3 of air that contains 1 mg/m^3 poses the same risk as ingesting 10 mg of the substance). How should intermittant exposures be converted to equivalent lifetime doses? Typically simple averaging is done (e.g., 1 year at 70 ppm is equivalent to 70 years at 1 ppm). Which studies and which subgroups of animals from the studies should be used for extrapolation? Typically studies with negative results are ignored, and the sex-dose groups with the highest incidence of cancer are used for extrapolation. Indeed, often the extrapolation is made not from the observed incidence, but rather from the upper 95 percent confidence limit of the observed incidence. These assumptions are likely to bias the risk estimates upward, perhaps by substantial margins.

In 1978, the CAG used the one-hit model and a surface-area conversion to extrapolate from the NCI high-dose male mouse data, yielding a lifetime risk estimate of 7.2 x 10^{-6} for continuous exposure to 1 ug/m^3 of EDC (Albert 1978). Arthur D. Little reports a more recent CAG risk estimate of 0.5 x 10^{-6} at a daily dose of 1 ug, based on NCI results with rats (Perwak et al.

1981). If we assume a daily intake of 24 m^3 of air per day, as the CAG did in its 1978 report, that translates to a lifetime risk of 12 x 10^{-6} for exposure to airborne EDC at a concentration of 1 ug/m^3. Crouch (1983), also using the NCI data for rats and a one-hit extrapolation, but using a weight conversion, estimates a lifetime risk of 3.4 x 10^{-6} for the same concentration of airborne EDC.

The effects of alternative assumptions about the appropriate method for dose conversion may be computed very easily. Had Crouch used the surface area conversion, his estimate would be 6 times higher. Similarly, had the CAG used the weight conversion, its estimates would be 6 times lower for the rat data and more than 13 times lower for the mouse data. For purposes of the benefit-cost analyses to be performed later, it is convenient to convert the lifetime risk estimates for exposure to 1 ug/m^3 to risk per ppb-person-year of exposure. To do this, we divide the lifetime risk estimates by 70 (the approximate number of years in an average lifetime) and multiply by 4.1 (the concentration in ug/m^3 that is equivalent to 1 ppb of EDC). Table 3 reports the results for the alternative estimates, which range from a low of 0.03 x 10^{-6} cancers per ppb-person-year (the CAG mouse estimate using a weight conversion) to 1.2 x 10^{-6} cancers per ppb-person-year (Crouch's estimate using a surface-area conversion).

The estimates in Table 3 vary by roughly a factor of 40. The true range of uncertainty, however, is substantially greater. Crouch (1983) argues that in extrapolating from one species to another, the confidence interval should encompass a factor of 5, even without taking account of uncertainty about whether or not

Table 3. Alternative Risk Estimates

Author	Species	Risk Factor (10^{-6} cancers/ppb-year) Weight	Surface area
CAG	Rat	0.12	0.70
Crouch	Rat	0.20	1.2
CAG	Mouse	0.03	0.42

Sources: See text.

the linear model is correct. With one of the standard non-linear models, the estimated risk at low doses would be far lower than any of the estimates in Table 3. These risk estimates also are likely to be biased upwards because they take no account of the negative results from Maltoni's inhalation studies.

In addition to the risk estimates based on the NCI animal studies, the CAG also computed a risk factor for EDC using an earlier risk assessment that it had performed for ethylene dibromide (EDB) based on a one-hit extrapolation from human epidemiological data (Albert 1978). Based on the assumption that EDB is 50 times as potent a carcinogen as EDC, the CAG estimated a risk factor of 0.7×10^{-6} per ppb-person-year. The CAG noted, however, that "this value appears to be an overestimate and should be used with caution" (Albert 1978, p. 31).

Control Options

A discussion of control options may seem premature to some readers given the limited information available on dispersive uses of EDC. Estimating the value of information, however, requires that we attempt to determine what options might be exercised if EPA proceeded to regulate. Several general strategies might be used to reduce the risks from dispersive uses of EDC. For some uses, process modifications or emission control techniques may be feasible. PVC manufacturers, for example, have been developing ways to reduce the frequency with which reactors must be cleaned. It may also be possible to improve the recovery rates for EDC used in reactor cleaning and in extraction

processes for pharmaceuticals. Improved ventilation or the use of respirators may offer significant reductions in occupational exposures, though ventilation could increase ambient concentrations and thus exposures for the general population. For many uses, however, the optimal (and in some cases, the only feasible) control method is likely to be substitution of other substances. It is impossible to tell at this point, however, what specific techniques would be most cost-effective for different uses.

Virtually no information exists on the costs of these alternative strategies. One consultant lists potential substitutes for EDC in various applications, but provides no information on the suitability of those substitutes; even relative price information is missing in most cases, because it is not clear what substitute would be used. We must also be alert to the possibility that the substitutes are themselves toxic, so that one of the "costs" of banning EDC could be increased use of other risky substances. One consultant, for example, lists PCE as a likely substitute for EDC in textile processing, but PCE is also a suspected carcinogen (Campbell, Cohan, and North 1982). Although the use of EDC in gasoline is not covered by this analysis, it is interesting to note that EDB has been suggested as a possible substitute for EDC in leaded gasoline, though as noted earlier the CAG estimates that EDB is roughly 50 times as potent a carcinogen as EDC (Albert et al. 1978).

Summary of Existing Information

As the discussion in this chapter makes clear, a great many uncertainties confront EPA officials in deciding what regulatory steps, if any, to take with regard to dispersive uses of EDC. Indeed, of the many parameters that would enter into an analysis of the benefits and costs of regulation, it is difficult to point to a single one that can be estimated with much confidence. Some of the key uncertainties probably cannot be resolved in the forseeable future. The most striking of these is the unit risk factor; additional animal studies might be of some help, but they would not deal with the fundamental sources of uncertainty -- the apropriate methods for extrapolating from high to low doses and from animals to people. Other uncertainties, however, could be reduced, though not eliminated, with additional effort and expense. Three classes of information appear to be both potentially important and possible to obtain: (1) the volumes of EDC employed in various dispersive uses; (2) exposure factors for different uses; and (3) the costs of control (including the costs of possible substitutes) for different use categories. The draft Section 8(a) rule would provide direct information only in the first category. It would, however, also provide a starting point from which the other two types of information might be acquired.

V. A DECISION-ANALYTIC STRUCTURE FOR EDC

To estimate the value of information that might be acquired on dispersive uses of EDC, we need to know how that information would affect decisions and, in turn, expected net benefits. The first section of this chapter develops a benefit-cost framework for evaluating the net benefits of regulating EDC. The second section presents an estimate of those net benefits for a set of base-case parameter values. The third section embeds the benefit-cost model in a simple decision tree to estimate the value of information that might be acquired under the Section 8(a) rule. The following section tests the sensitivity of the results to alternative parameter values. We then extend the tree to consider other information that might be gathered, either subsequent to the 8(a) rule or as part of it.

A Benefit-Cost Framework

Ultimately, EPA must decide whether or not to regulate dispersive uses of EDC. It can make that decision now, or it can postpose it until additional information has been acquired. For convenience, we follow the usual convention in benefit-cost analyses and define the net benefits of the status quo ("no regulation") to be zero; the net benefits of all of the alternatives are measured relative to that status quo. Thus, for example, higher risks due to higher exposure levels appear in our calculations as higher benefits for "regulation" rather than as higher costs for "no regulation."

For simplicity, we shall assume that regulation by EPA of dispersive uses of EDC would take the form of banning some or all such uses; the stringency of the regulation is summarized by the fraction of dispersive uses banned, F, which can range from 0 to 1. This is, admittedly, a gross oversimplification of the regulatory options that might be exercised, particularly if one considers the full range of alternatives available to other agencies (such as OSHA) and other branches of EPA (such as OAQPS). Alternatively, the reader may think of F as a more general measure of the stringency of regulation that represents the proportion by which emissions are reduced.

Benefits. The benefits of regulating EDC consist almost exclusively of reductions in the number of premature deaths from cancer. Noncancer effects are unlikely to be of concern at the exposure levels in question, and we assume that virtually all cancer cases lead to death. Estimating those benefits requires several steps, as illustrated in Figure 4. The first step is to determine the fraction, F, of dispersive uses to be banned. That, together with the quantity of EDC in dispersive use, Q, determines the amount by which use is reduced. The amount by which emissions are reduced depends on the fraction of EDC that is emitted, M. Reduced exposures are the product of reduced emissions and the exposure factor, X, which gives the number of ppb-person-years of exposure per kilogram of EDC emitted. The reduction in risk depends on the dose-response function; we assume that expected risk is proportional to exposure, where R is the risk per ppb-person-year of exposure. Finally, the benefit

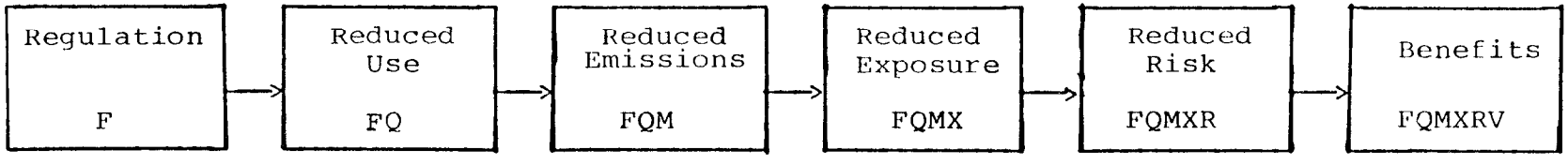

Figure 4. Steps in Estimating Benefits of Regulation

in dollar terms is the reduction in risk times the shadow price placed on reducing risk, V. Thus, the total benefit of banning the fraction F of dispersive uses is:

$$B(F) = Q \times F \times M \times X \times R \times V. \quad (7)$$

Note that in this formulation, the total benefit is proportional to the quantity of EDC employed in dispersive uses.

Annual Costs. In benefit-cost analysis, the appropriate measure of the costs of an action is the sum of the losses in consumer's and producer's surpluses. Here we assume that the loss in producer's surplus from banning some dispersive uses of EDC is zero. In essence, we assume that the supply curve is perfectly elastic over the relevant range; given the small fraction of total EDC production devoted to dispersive uses, this assumption is not unreasonable. To the extent that it is inaccurate, it biases the decision in favor of regulation.

The loss of consumer's surplus from a partial ban depends in part on which dispersive uses are forbidden. For simplicity, we assume that the lowest-value uses would be banned first.[5] (A tax on dispersive uses of EDC would accomplish this result automatically.) The loss in consumer's surplus is shown by the shaded area in Figure 5. Algebraically, if the demand curve is linear and the elasticity is e at the original equilibrium, that area is:

$$C(F) = .5F^2(PQ)/e. \quad (8)$$

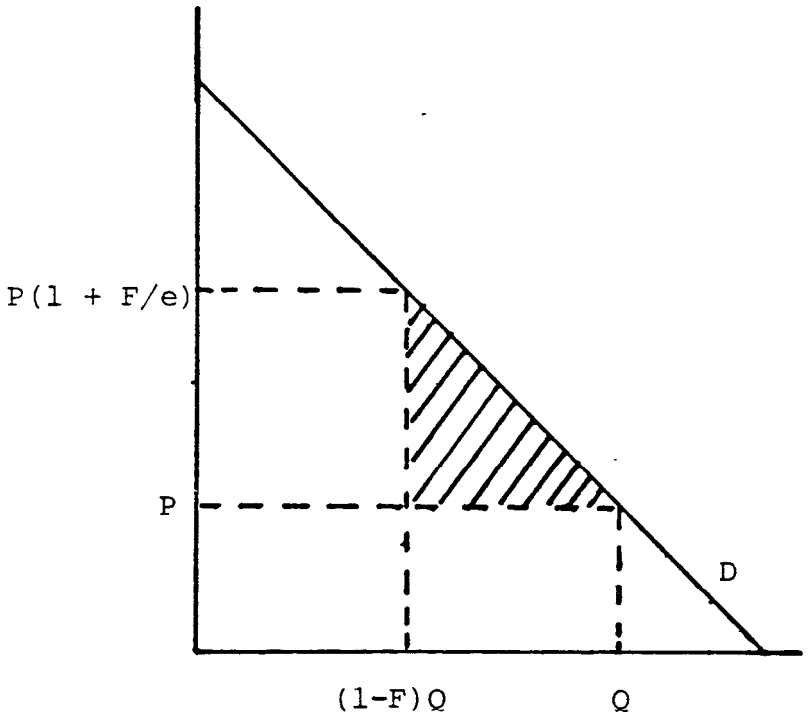

Figure 5. Loss in Consumer's Surplus from a Partial Ban

Note that the lower the elasticity of demand (i.e., the steeper the demand curve), the greater the loss in consumer's surplus. The elasticity of demand for EDC in dispersive uses will depend on a variety of factors, including the prices and suitabilty of substitutes, and the elasticities of demand for the final products incorporating EDC. Note, also, that while the cost is proportional to Q, it rises with the square of the fraction banned; the marginal cost of tightening the regulation is increasing.

Promulgation Costs. In addition to the continuing, annual costs described above, promulgation of a regulation also entails some fixed, one-time costs. Although most analyses ignore these costs, they are not inconsequential. Before proposing regulations, EPA must expend resources, both "in house" and through consultants, to study control alternatives; to gather information on exposure, risk, and other factors; and to write the regulations themselves. After a regulation has been proposed, EPA must hold hearings, evaluate information submitted by interested parties, and then promulgate a final rule. The affected industries usually also expend considerable resources disputing the need for the regulation. Often fairly elaborate alternative studies are commissioned and highly paid experts are retained to offer oral and written testimony in opposition to the EPA proposal. Environmental groups also may participate, arguing either for the EPA proposal or for a more stringent one. After a regulation has been promulgated, suits may impose substantial legal costs on the various parties.

In the model, we denote these one-time costs of promulgation as C_P. EPA officials also have stated to us, however, that they believe that prior to beginning to formulate control regulations for EDC, they would need more information on dispersive uses. Such information could be acquired either by a Section 8(a) rule or, less accurately, by a survey of firms. The conduct of a survey would be complicated by the fact that the Agency does not have a very good idea of which firms should be solicited for information. In contrast to a Section 8(a) rule, firms also would not be under any compulsion to respond to a survey. We denote the one-time cost of a survey as C_S. For comparison with the ongoing costs and benefits, these one-time expenses must be annualized by multiplying them by a factor, k, which is a function of the discount rate and the time horizon. More specifically,

$$k = 1/[\sum_{t=1}^{n} (1+r)^{-t}] \quad , \tag{9}$$

where r is the discount rate and n is the time horizon.

Net Benefits. With the benefit and cost functions described above, the annual net benefit of banning the fraction F of dispersive uses is:

$$\begin{aligned} N(F) &= QFMXRV - .5F^2PQ/e - k(C_P + C_S) \\ &= Q(FMXRV - .5F^2P/e) - k(C_P + C_S) \end{aligned} \tag{10}$$

To simplify future expressions, let us introduce some additional notation: b = MXRV is the benefit of eliminating one kg of EDC in

dispersive use, and a = 0.5(P/e) is the coefficient of the cost function. Equation (10) then may be written:

$$N(F) = Q(bF - aF^2) - k(C_P + C_S) \quad . \tag{11}$$

The optimal level of regulation, F, is found by differentiating equation (11) with respect to F:

$$dN(F)/dF = 0 = Q(b - 2aF). \tag{12}$$

Solving for F yields the optimal level of control:

$$F^* = \begin{cases} 0.5b/a, \text{ if } 0.5b/a \leq 1 \\ 1.0, \text{ otherwise.} \end{cases} \tag{13}$$

Note that the optimal level of control is independent of Q; that reflects the facts that in our formulation the net benefit is a linear function of Q and the cost of promulgating the regulation is fixed. This independence proves to be important for computational purposes, as it means that expected net benefits can be computed knowing only the expected value of Q over the relevant range.

Equation (13) gives the optimal level of control <u>if</u> EPA regulates. The annual net benefits of regulation, however, may not be sufficient to justify the fixed costs of promulgation. To see if they are, set equation (11) equal to zero and solve for the minimum quantity:

$$Q(bF-aF^2) - k(C_P+C_S) = 0 \quad , \tag{14}$$

which yields

$$Q_{min} = k(C_P+C_S)/(bF-aF^2) \quad . \qquad (15)$$

TO summarize, if $Q < Q_{min}$, it is better to stop than to regulate. If $Q > Q_{min}$, it is better to regulate at the level F* defined in equation (13). If any of the parameter values are uncertain, the expected values may be substituted in the above statements and equations. For example, if Q is uncertain, equation 11 gives expected net benefits if we substitute E(Q) for Q.

Base-Case Results

As the discussion in the previous chapter made clear, virtually all of the parameter values in the model are highly uncertain. Moreover, the nature of the uncertainty is such that it is extremely difficult to specify prior distributions on those values that can be defended with much confidence; any estimates must be highly subjective. For the purposes of this case study, we have relied on our own judgment, as informed by the studies discussed in the previous chapter, and, in several cases, on estimates from officials at EPA. More extensive consultations with experts in the relevant fields might be desirable, though potentially costly. Table 4 presents our base-case estimates.

Benefit Estimates. The greatest uncertainty surrounds the benefit estimates. We have assumed an emission factor of M = 1.0; i.e., that all of the EDC consumed in dispersive uses is

Table 4. Base Case Parameter Values

Parameter	Definition	Units	Base Value
Benefits			
M	emission factor	none	1.0
X	exposure factor	ppb-years/kg	1.3
R	risk factor	deaths/ppb-year	0.4×10^{-6}
V	value of saving a life	$/life saved	1×10^{6}
b	b=MXRV	$/kg	0.5
Annual Costs			
e	demand elasticity	none	1.0
P	price of EDC	$/kg	0.303
a	a=.5P/e	$/kg	0.15
One-Time Costs			
C_P	promulgation cost	$1000	5,000
C_8	section 8 cost	$1000	500
C_S	survey cost	$1000	400
k	annualization rate	none	0.10

emitted. This obviously is an upper bound, as it is impossible for M to exceed unity. It is also our best estimate, however, to one significant digit.

The exposure factor is highly uncertain. We have broken our estimate into two components: exposure to the general public, X_G, and exposure to workers, X_W. The overall exposure factor, X, is simply the sum of those two components. For the general population, we estimate an exposure factor of X_G = 0.3 ppb-person-years/kg, which is roughly the middle of the range of the values discussed in the previous chapter. The exposure factor for workers is far more difficult to estimate. Our estimate of X_W = 1 ppb-person-year/kg is substantially lower than Campbell, Cohan, and North's (1982) implicit estimate for PCE used in dry cleaning plants. That reflects our beliefs that Campbell, Cohan, and North's estimate probably is too high for PCE and that the exposure factor for EDC is much lower than that for PCE because plants where EDC is used are likely to have fewer workers and to be better ventilated than most dry cleaning establishments. Summing the two components yields our estimate of the overall exposure factor, X = 1.3.

The unit risk factor, 0.4×10^{-6} cancers/ppb-person-year, is a simple average of the risk factors presented in Table 3. Implicitly, we have given equal weight to Crouch's estimate, the two CAG estimates, and the two alternative methods of dose conversion. (By chance, a simple average of Crouch's original estimate and the two original CAG estimates gives the same

result.) To the extent that one assigns a non-zero probability to the non-linear dose-response models' being correct, this estimate is too high.

The final component of the benefit estimate, V, the value of preventing a case of cancer, is highly subjective and controversial. The value used here, $1 million, lies approximately in the middle of the range of values estimated in empirical studies of willingness-to-pay for risk reduction (see Haigh, Harrison, and Nichols 1983 for a brief discussion of these studies). Many analysts, however, would regard it as a high estimate, particularly for a program to reduce exposure to a carcinogen, where the lag between expenditures and the receipt of health benefits often is long, and the "lives saved" are relatively short because cancer is disproportionately a disease of the elderly.

Multiplying together the four parameters yields an estimate for b of $0.5/kg of EDC controlled.

Cost Estimates. The ongoing unit costs of control in our model are a function of two parameters, the price of EDC and the elasticity of demand for EDC in dispersive uses. The price, P = $0.303/kg, was obtained in August 1982 from an official at Dow Chemical. The elasticity estimate, e = 1, is arbitrary, as we have been unable to obtain any empirical estimates. Dividing the price by the elasticity and multiplying the result by 0.5 yields an estimate of a = $0.15/kg. Although we are uncomfortable with this estimate, the results turn out to be relatively insensitive to it, as we show later.

The cost of promulgation, c_P = $5 million, is based on discussions with officials at EPA, who estimated that a "minor" regulation such as this one would cost the agency roughly $3-4 million to promulgate, of which about $1 million would have been spent prior to the point at which our hypothetical decision would be made. Thus, the estimated incremental cost of promulgation to EPA is $2.5 million. As a rough guess, we doubled that figure to account for costs borne by other parties and to allow for the possibility of post-promulgation litigation.

The estimated cost of a survey in lieu of a Section 8(a) rule, c_S = $400,000, also as based on discussions with EPA officials, who suggested a range of $250,000 to $500,000 (not including the costs to firms of responding to the survey).

The annualization factor, k, depends on the discount rate and the time horizon, as shown earlier in equation (9). Table 5 shows the values of k that correspond to discount rates of 3, 5, and 10 percent, and time horizons ranging from 5 years to infinity. An infinite horizon is inappropriate here, because any regulation is likely to become obsolete over time as technologies change. Our estimate of k = 0.1 is based roughly on a discount rate of 5 percent and a time horizon of 15 years.[6]

Volume Estimate. For the purposes of our crude benefit-cost analysis, we need an estimate of the average annual consumption of EDC in dispersive uses over the next decade or so. The latest available figure is SRI's estimate that dispersive uses totaled no more than 3.75 to 4.75 million lbs (1.7 to 2.2 million kg) in 1979 (Gibson et al. 1981). The evidence available also suggests,

Table 5. Annualization Factors

Discount Rate(%)	Time Horizon (years)				
	5	10	15	20	
3	0.22	0.12	0.08	0.07	0.03
5	0.23	0.13	0.10	0.08	0.05
10	0.26	0.16	0.13	0.12	0.10

however, that usage declined substantially during the mid to late 1970s; the Auerbach estimate for 1977 was roughly twice as high (Seufert 1979). If that annual rate of decline has continued, the estimate for the mid 1980s would be substantially less than 500,000 kg, most of which would be used for PVC reactor cleaning. Two factors urge caution in extrapolating that rate of decline, however. First, the Auerbach estimate may well have been too high for 1977. Second, the release of the NCI results may have caused a one-time drop in usage, so the apparent decline was not a continuing phenomenon. Nonetheless, both the quantitative estimates available and the qualitative evidence that actual dispersive uses are so hard to identify lead us to believe that the volume of use in the mid 1980s will be quite low, whether or not EPA or other agencies promulgate new control regulations. Our median estimate is about 600,000 kg (i.e., if asked to bet on whether the true quantity in, say, 1985 would be more or less than 600,000 kg, we would be indifferent as to which side of the wager we took). Our subjective prior distribution, however, is fairly "flat" and skewed to the right; we believe that there is a reasonable chance that actual usage could be much higher. As a result, our best estimate for the expected quantity is higher than our median; we estimate E(Q) to be about 800,000 kg per year. Later, in analyzing the value of information that might be acquired under an 8(a) rule, we shall define our subjective prior distribution more formally and completely.

Calculation of Net Benefits. We are now prepared to estimate the expected net benefits of a control regulation for

dispersive uses of EDC. Given our estimates of a and b, the optimal level of regulation is $F^* = 1.0$; i.e., with our base parameter values, if EPA regulated at all, it would be optimal to ban all dispersive uses. The expected net benefit (from equation 11) is then:

$$E[N(F)] = E(Q)\,[bF - aF^2] - k(C_P + C_S) \qquad (16)$$
$$= (800{,}000)[0.5 - 0.15] - 0.1(5{,}000{,}000 + 400{,}000)$$
$$= -\$260{,}000.$$

Thus, with our base-case estimates, regulation would not be justified in terms of expected net benefits. This result primarily reflects small benefits and high one-time costs, rather than high ongoing control costs. Our base-case parameter values predict that a complete ban of EDC in dispersive uses would prevent about one death every two and one-half years, mostly due to reduced mortality among workers exposed to EDC on the job.

Some simple sensitivity analyses suggest that our conclusion is not very robust. If, for example, the quantity of EDC in dispersive uses were twice as high as our expected value, the estimated net benefits of regulation would be:

$$E[N(F)] = (1{,}600{,}000)[0.5 - 0.151 - 0.1(5{,}000{,}000+400{,}000) \qquad (17)$$
$$= +\$20{,}000.$$

Similarly, if the marginal benefit of controlling EDC were twice as high as our base-case estimate (due, for example, to V = $2

million rather than $l million, or to use of one of the higher risk estimates based on a pure surface area extrapolation from rat to man), estimated net benefits also would be positive:

$$E[N(F)] = (800,000)[1.0 - .15] - 0.1(5,000,000 + 400,000) \quad (18)$$

$$= +\$140,000.$$

Equally plausible sensitivity analyses in the other direction, of course, would make regulation look even less attractive than it does in the base case. This wide range of plausible results suggests that additional information that narrows the range of uncertainty may be of significant value.

The Value of Information: A Simple Decision Tree

The proposed Section 8(a) rule would allow EPA to revise and refine its estimates of the volumes of EDC employed in various dispersive uses. The primary value of such information would be to help EPA and other agencies (particularly OSHA) determine whether dispersive uses are of sufficient magnitude to justify the costs of regulation or additional investigation. In addition to updating our estimate of Q, however, the rule also might allow us to refine some of the other parameter estimates. If, for example, virtually all of the volume was found to be used for PVC reactor cleaning, that would lead us to lower our estimate of the exposure factor. In contrast, if it turned out that substantial amounts of EDC were incorporated in consumer products, we would estimate a higher exposure factor than at present. Information on volumes of dispersive uses also would allow EPA to determine

where it might be worthwhile to spend additional resources measuring exposure levels and getting better information on control options and costs.

In this section, we focus only on the quantity information provided by the rule. More specifically, we assume that the rule would provide information only on the total quantity of EDC in dispersive uses, and that after obtaining quantity information EPA would have to decide whether or not to regulate without the option of gathering any more information. Although these assumptions are overly restrictive, they preserve the bare esentials of the problem and allow us to illustrate the basic decision analytic framework.

Basic Structure of the Tree. We assume that EPA initially has three alternatives: (1) It can stop all of its activities with respect to dispersive uses of EDC. (2) It can regulate "immediately," banning some or all uses. (3) It can promulgate an 8(a) rule, postponing the decision to regulate until it has received information on total volume. Figure 6 presents the basic decision tree. The expressions in square brackets at the ends of the branches represent annual net benefits. As before, by convention the status quo, "Stop," provides zero net benefits.

Calculations in bottom branch, "Regulate Now," are the same as before. As discussed above, if the Agency decides to regulate it must then determine the stringency of the regulation, F. (There is an infinite range of possibilities here: we show only one representative branch.) Once that decision is made, the net benefits depend on the true values of the quantity (Q) and the

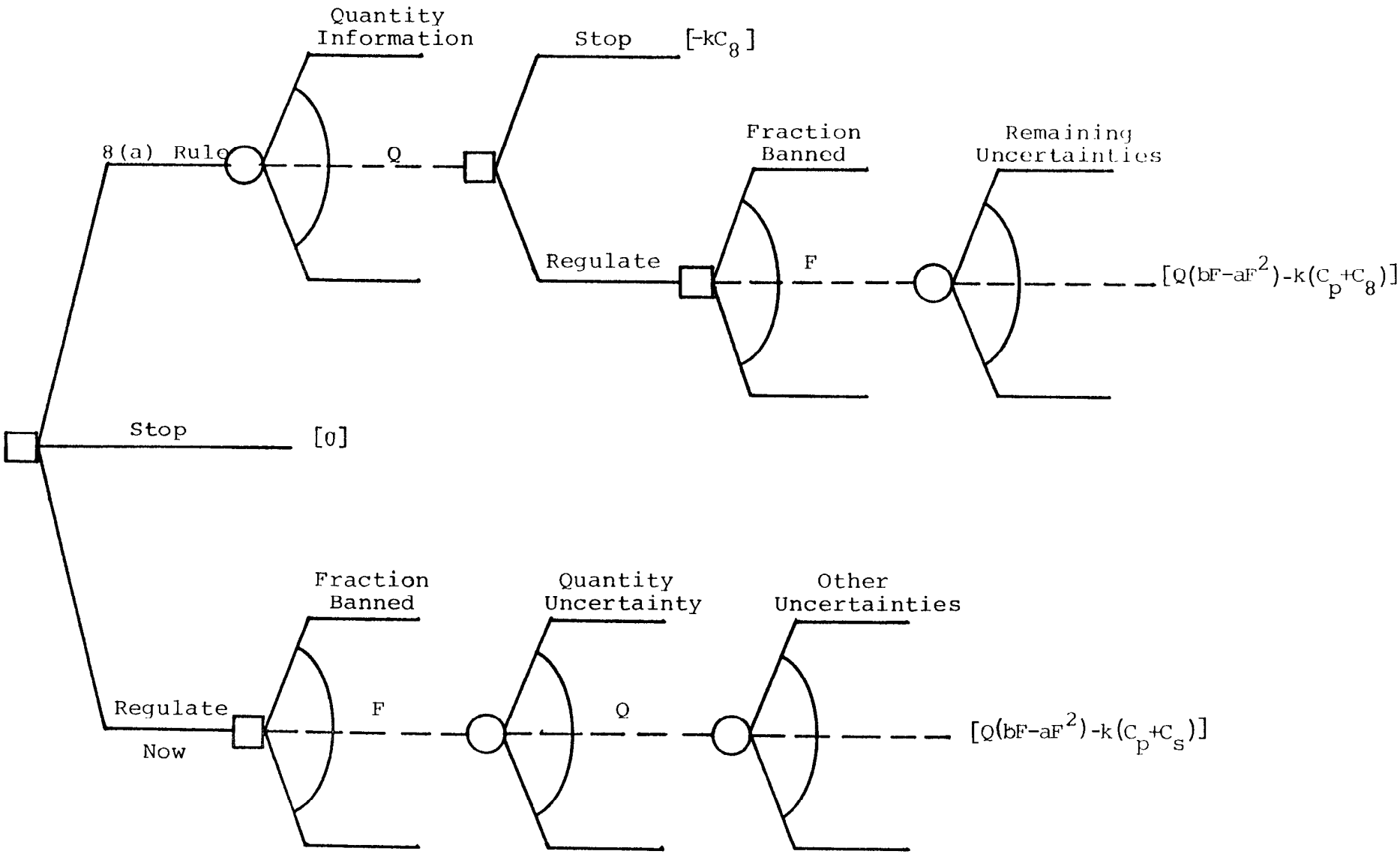

Figure 6. The Basic Decision Tree for EDC

other uncertain parameters. (Again, we show only one representative branch.) To find the expected net benefits of "Regulate Now," we "average out" the branches.

The value of the decision-analytic approach comes in evaluating the upper branch, the "8(a) Rule." After the rule has been imposed, the information obtained is used to update the estimate of the total volume, $\hat{Q}$. In general, $\hat{Q}$ will not be a perfect estimate of Q; for reasons discussed earlier, having to do with less-than-complete responses from firms and inaccurate reporting, an 8(a) rule will not provide perfect information on current levels of use. Additional uncertainty is introduced by the fact that we need to project "typical" use levels over the next decade or so. For the moment, however, we shall assume that the 8(a) rule provides perfect information on Q; thus, our prior distribution on $\hat{Q}$ is the same as our prior on Q, $f(\cdot)$. As discussed in Chapter 2, the expected value of perfect information can be useful in providing an upper bound estimate of the value of the actual (imperfect) information.

Once $\hat{Q}$ has been determined, the Agency must decide whether or not to regulate. In general, we would expect high values of $\hat{Q}$ to lead to regulation and low values to lead to stopping. The minimum quantity needed to justify regulation after the Section 8(a) rule has been imposed can be calculated easily. The net benefits of regulating are given by:

$$N(F) = \hat{Q}(bF - aF^2) - k(C_P + C_8) \quad . \tag{19}$$

The net benefits of not regulating are simply $-kC_8$. Thus, for regulation to be justified after the request, we must have

$$\hat{Q}(bF - aF^2) - k(C_P + C_8) \geq -kC_8 \quad , \tag{20}$$

or

$$\hat{Q} \geq kC_P/(bF - aF^2) \quad . \tag{21}$$

Note that the costs of the 8(a) rule ($-kC_8$) cancel out and do not affect this decision; at the point this decision is made, the 8(a) costs are sunk and thus irrelevant for decision making. The key advantage of the 8(a) branch is that the Agency knows Q before it must decide whether or not to regulate. As compared to "Regulate Now," it also avoids the cost of a survey of uses. Its disadvantage, of course, is that the 8(a) rule imposes costs on both EPA and firms.

Parameter Values. We already have estimated most of the parameter values needed to compute the expected values of the alternative strategies (Table 4). We now need to specify more precisely our prior distribution on Q and to estimate the cost of the Section 8(a) rule.

As discussed earlier, our prior subjective distribution on Q is relatively flat and skewed to the right; our median estimate is fairly low, but we would not be "surprised" to learn that the actual quantity was substantially higher. Our analysis will be simplified considerably if we specify a functional form for our prior. The log-normal distribution offers several attractive features: it is bounded below by zero (negative quantities are

impossible); it is skewed to the right, with the mean higher than the median; and it is widely used to represent uncertainties such as these. More specifically, we assume that ln(Q) is distributed normally, with mean u and variance s^2. The median of that distribution is exp(u), where $\exp(u) = e^u$, while the mean is exp(u + $s^2/2$). Changing ln(Q) by one standard deviation changes the value of Q by a factor of exp(s).

Our estimate of the expected value of Q is 800,000 kg, which implies that u + $s^2/2$ = ln(800,000). Our estimate of the variance of ln(Q), s^2 = 0.5, reflects our substantial uncertainty about the true value of Q. With s^2 = 0.5, the standard deviation of ln(Q) is s = 0.71. Thus, each standard deviation of our prior on the quantity represents a factor of exp(0.71) = 2.0. Table 6 shows selected percentiles of our prior on Q. Note that our median estimate is slightly over 600,000 kg. Our 95 percent confidence limits, however, cover a broad range, from less than 160,000 kg to more than 2.5 million kg (about 5.6 million lbs.).

Our estimate of the one-time cost of a Section 8(a) rule has several components. First, EPA estimated that the cost to firms of responding to the rule would be no more than $135,000, based on a maximum of 1000 firms having to comply with the rule. As we suspect that substantially fewer than 1000 firms would in fact respond, that estimate almost certainly is too high. It does not, however, include costs to firms that do not ultimately respond, but which incur expenses inquiring about the rule. The second component is the cost to EPA of preparing the reporting forms, answering inquiries, analyzing the responses, and then projecting actual use and deciding whether or not to proceed with

Table 6. Percentiles of Prior on Q

Percentile	Q(1000 kg)
2.5	156
10.0	252
25.0	387
50.0 (median)	623
75.0	1,004
90.0	1,542
97.5	2,491

further steps. Based on discussions with EPA officials, we estimate that cost to be at least $125,000. The final component is the cost of promulgating the 8(a) rule itself. The Agency must draft the rule, have it approved by the Office of Management and Budget, publish it, respond to comments, and then promulgate the final rule. An EPA official suggested, as a rough guess, that these 8(a) promulgation costs would total about $250,000. Adding these three components together yields our estimate of c_8 = $500,000.

Numerical Results. Net benefits for "Stop Now" are, of course, 0. As shown earlier, with the base-case parameter values "Regulate Now" yields expected net benefits of -$260,000; the expected quantity, E(Q)= 800,000 kg, is too small to justify the fixed costs of regulation. Calculation of the expected net benefits for the 8(a) branch is slightly more complicated, and deserves some explanation.[7]

In this formulation, the 8(a) rule only provides information on the quanitity. Thus, it determines whether or not regulation will be imposed, but not how stringent the regulation will be if it is promulgated; the optimal degree of stringency (F) is independent of Q. As shown earlier, with the base case parameter values, all dispersive uses should be banned ($F^* = 1.0$). Using equation (21), we can calculate the minimum quantity needed to justify regulation after the Section 8(a) rule:

$$Q \geq 0.1(5{,}000{,}000)/[0.5(1.0) - 0.15(1.0^2)] \qquad (22)$$
$$= 1{,}428{,}571 \ .$$

In other words, the Section 8(a) rule will alter the decision to "Stop" (the best alternative given existing information) only if it reveals that the quantity is in in excess of 1.4 million kg. Given our prior on Q, the expected value of the quantity conditional on its being larger than 1.4 million kg is 2.13 million kg. Thus, conditional on finding a Q large enough to justify regulation, and disregarding (for the moment) the cost of the 8(a) rule itself, the expected net benefit of regulation is:

$$2{,}131{,}000(0.5 - 0.15) - 0.1(5{,}000{,}000) = \$246{,}000. \qquad (23)$$

Given our prior on Q, however, the probability of dicovering that Q is greater than 1.4 million kg is only 0.12. Thus the expected benefit of the 8(a) rule is 0.12($246,000), or less than $30,000. Against that expected benefit must be set the annualized cost of the 8(a) rule, which is 0.1($500,000) = $50,000. Thus the expected net benefit of the 8(a) strategy is -$20,000 per year; the best strategy remains "Stop Now," with net benefits of zero. Given the many other uncertainties in the problem, however, this result is far from conclusive.

Sensitivity Analyses

Even our highly pruned tree has many parameters, each of which is a potential candidate for a sensitivity analysis. Fortunately, for analytic purposes we can restict our attention to seven of them: (1) b, the marginal benefit per unit of EDC banned (b is in turn a function of four parameters, but varying anyone of them by a given factor has the same effect on b and

thus on the net benefits); (2) the mean of our prior on Q, E(Q) (this is a function of u and s^2 -- we shall vary u); (3) the variance of our prior on ln(Q), s^2; (4) the cost coefficient, a (which is a function of two parameters, but as with the benefit parameter, varying either one has the same impact on a); (5) C_p, the cost of promulgation; (6) the cost of the Section 8(a) rule, C_8; and (7) the capitalization factor, k.

With our base case values, the 8(a) rule yields negative expected net benefits. Table 7 lists the parameters of interest and their base values. The column labeled "break-even value" shows the value of each parameter (holding the others fixed at their base levels) for which the 8(a) strategy just breaks even. Thus, for example, if b = 0.57, the 8(a) strategy and "Stop" yield the same expected net benefits (0); for higher values of b, the 8(a) strategy is preferred. Table 7 also reports the expected annual net benefits of the 8(a) strategy if we vary any of the individual parameters by $\pm$50 percent from its base-case value. For example, if b is 50 percent lower than our base case estimate (i.e., b = 0.25), the expected net benefit of the 8(a) rule is about -$50,000; as the annualized cost of the 8(a) rule is $50,000, that means that the expected value of the information provided is almost nil. In contrast, if the estimate of b is 50 percent higher (i.e., b = 0.75), the expected net benefit of the 8(a) rule is +$76,000.

The results in Table 7 should be interpreted with caution, as the degrees of uncertainty vary markedly across the different parameters. Net benefits appear to be relatively sensitive to the capitalization factor (k), for example, but uncertainty about

Table 7. Sensitivity Analysis

Parameter	Units	Base Value	Break-even Value	Net Benefits with ±50% Change in Parameter Value	
				-50%	+50%
b	$/kg	0.5	0.57	-50	+76
E(Q)	1000 kg	800	958	-47	+41
s^2	none	0.5	0.81	-39	-4
a	$/kg	0.15	0.08	+2	-36
C_P	$1000	5,000	3,761	+39	-38
C_8	$1000	500	296	+5	-45
k	none	0.1	0.084	+64	-63

that parameter is fairly small; k = 0.05, for example, requires a low discount rate and a very long time horizon (e.g., 5 percent and an infinite horizon, or 3 percent and a 31-year horizon). In contrast, the results are less sensitive to our estimate of the expected value of Q, E(Q), but we are much more uncertain about that parameter.

The most important source of uncertainty clearly is the marginal-benefit parameter, b. Variations in b have a large effect on expected net benefits, and we are highly uncertain as to its value, in particular because b is the product of four parameters, the value of each of which is very uncertain. In a later section in this chapter, we consider explicitly the value of acquiring information that allows EPA to refine its estimate of b.

Imperfect Information

Our analysis thus far has assumed that the 8(a) rule would provide perfect information on the quantity of EDC employed in dispersive uses. As discussed earlier, however, the actual information provided will be far from perfect, either as to current levels of use or, more emphatically, as to future use levels. Thus, we need to explore how reduced accuracy affects the value of the 8(a) rule.

Under the assumption of perfect information, our prior subjective distribution on $\hat{Q}$ (the estimate of the quantity that will be made after the 8(a) rule) is the same as our prior on the true Q. If the information is imperfect, however, the two

distributions will not be the same. A formal treatment of uncertainty would require that we specify the joint distribution of the true value of Q and the error in the estimate, and from that calculate the distribution of the post-rule estimate of the expected value of Q.

A much less complicated approach is to approximate the effect of imperfect information by reducing s^2, the variance of ln(Q). The intuitive explanation is that if the information is imperfect, the 8(a) information will have less impact on our estimate of the expected value of Q. A simple, discrete example illustrates the argument. Suppose we believe that it is equally likely that some parameter value is 0 or 100. Thus, the mean of our prior is 50. We now perform a test (gather information). If the test is perfect, after conducting it we will know the parameter value with certainty; the mean of our posterior will be 0 or 100, each with probability 0.5. Now suppose that the test is imperfect; it is right only 75 percent of the time. If the test says "high," there is still a 25 percent chance that the true value is 0; thus, a "high" result will change our estimate of the expected value of the parameter to 75, not to 100. Similarly, a "low" result will change our estimate to 25, not 0. Thus our prior on the post-test mean is clustered more tightly around our original estimate.

Using this approach, perfect information corresponds to our original estimate of $s^2 = 0.5$, while at the other extreme $s^2 = 0$ corresponds to the case where the 8(a) rule is so inaccurate that it provides no information. Figure 7 plots the expected annual net benefit of the 8(a) rule as a function of s^2; it falls from -

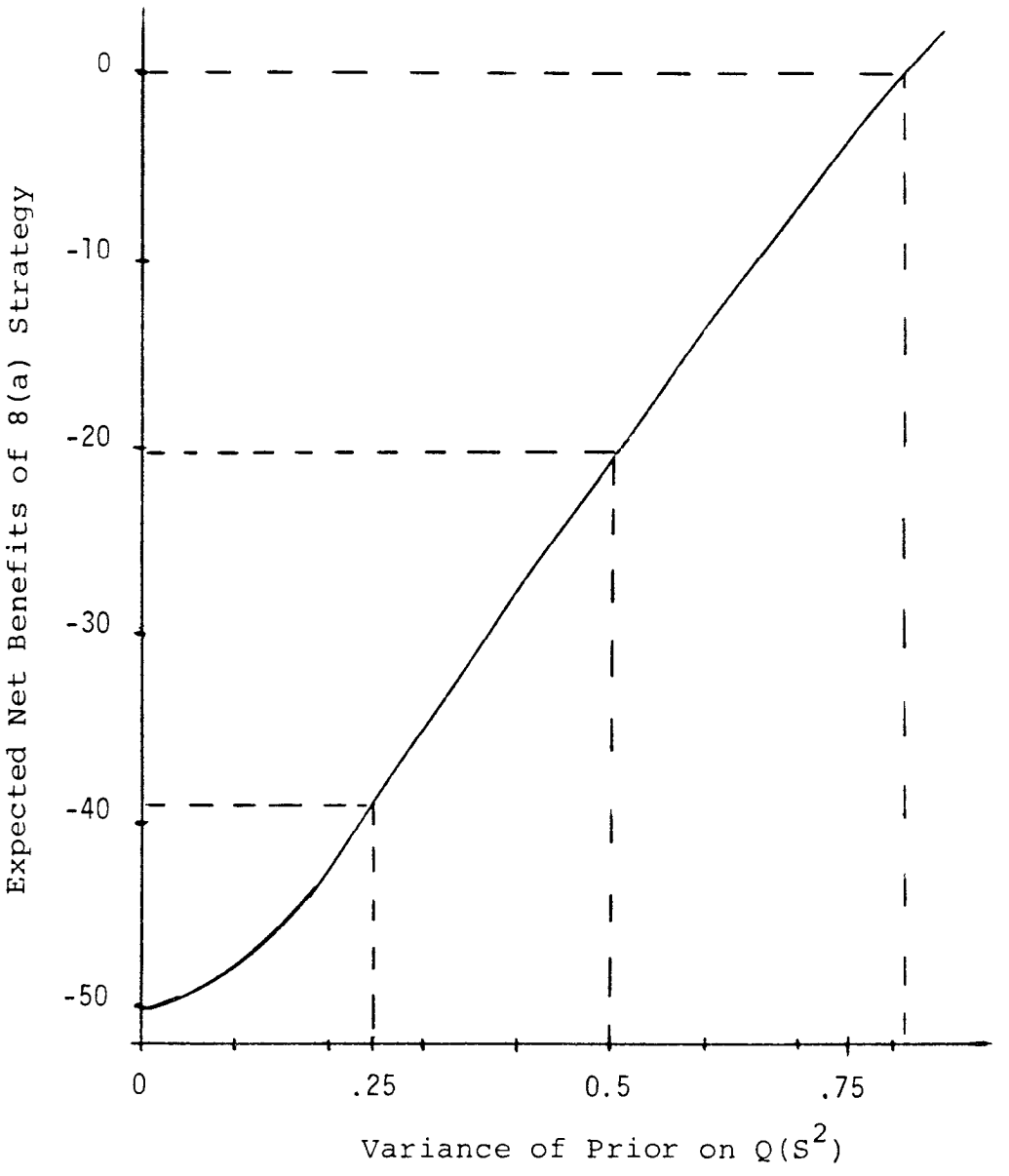

Figure 7. Sensitivity of Variance of Prior Distribution on Q

$20,000 for our base-case value of $s^2 = 0.5$, to -$48,000 for $s^2 = 0.1$.[8] It is difficult to determine which value of s^2 best represents the fact the 8(a) rule would provide highly imperfect information. It seems reasonable to suppose, however, that the variance in the prior on the post-rule estimate is no more than one-half as great as that in the prior on the true quantity; that would imply that $s^2 \leq 0.25$. With $s^2 = 0.25$, the expected net benefit of the 8(a) strategy is -$39,000; that is, the expected value of the imperfect information is only about $11,000, while its estimated annual cost is $50,000. Thus, taking account of the imperfect nature of the information provided by the rule lowers its value substantially.

Extending the Tree -- Other Information

In our basic decision tree, we have assumed that once an 8(a) rule has been issued and the results analyzed, a decision must be made whether or not to regulate. If the decision is made to regulate, EPA is committed to incurring the full costs of promulgation. A substantial portion of the costs of promulgation, however, would be for gathering additional information, information that could affect the desirability of regulation. Moreover, the costs of promulgation include several components that need not be undertaken simultaneously. Thus, one possibility after obtaining the 8(a) information is to undertake some of the studies necessary for proposing a control regulation, and then evaluate the results of those studies before making a decision whether to proceed with the additional steps required

for promulgation. This process could be broken up into many small steps; when one considers alternative sequences of studies, the number of potential strategies becomes very large, and the decision analytic structure quickly becomes unmanageable.

For illustrative purposes, we focus on only one type of information. If EPA decided to proceed toward regulation after getting the results of an 8(a) rule on volume and use, a logical next step would be to gather better data on exposure levels. This effort probably would involve a mix of dispersion modeling for different types of plants and sites, monitoring of ambient concentrations near dispersive uses, and monitoring of worker exposures (though the last might be sponsored by OSHA or NIOSH rather than EPA). In terms of our benefit-cost model, the effect of such studies would be to update (and possibly alter) our estimate of the exposure factor (X). Changing X would in turn change the estimate of the unit benefit parameter (b). EPA could then decide whether or not to commit itself to the expenditures necessary to promulgate a control regulation.

Figure 8 presents the resulting decision tree. EPA initially has two options: it can "Stop" or it can promulgate the 8(a) rule. (We have eliminated "Regulate Now" as an option, as our earlier analyses suggest it is extremely unlikely to yield positive net benefits.) If it follows the 8(a) strategy, EPA receives (imperfect) information on the quantity. The Agency must then decide whether to gather information on exposure or to stop. If it stops, the net benefit is $-kC_8$, the annualized cost of the 8(a) rule. If it continues, it receives information on exposure, which allows it to refine its estimate of b. At that

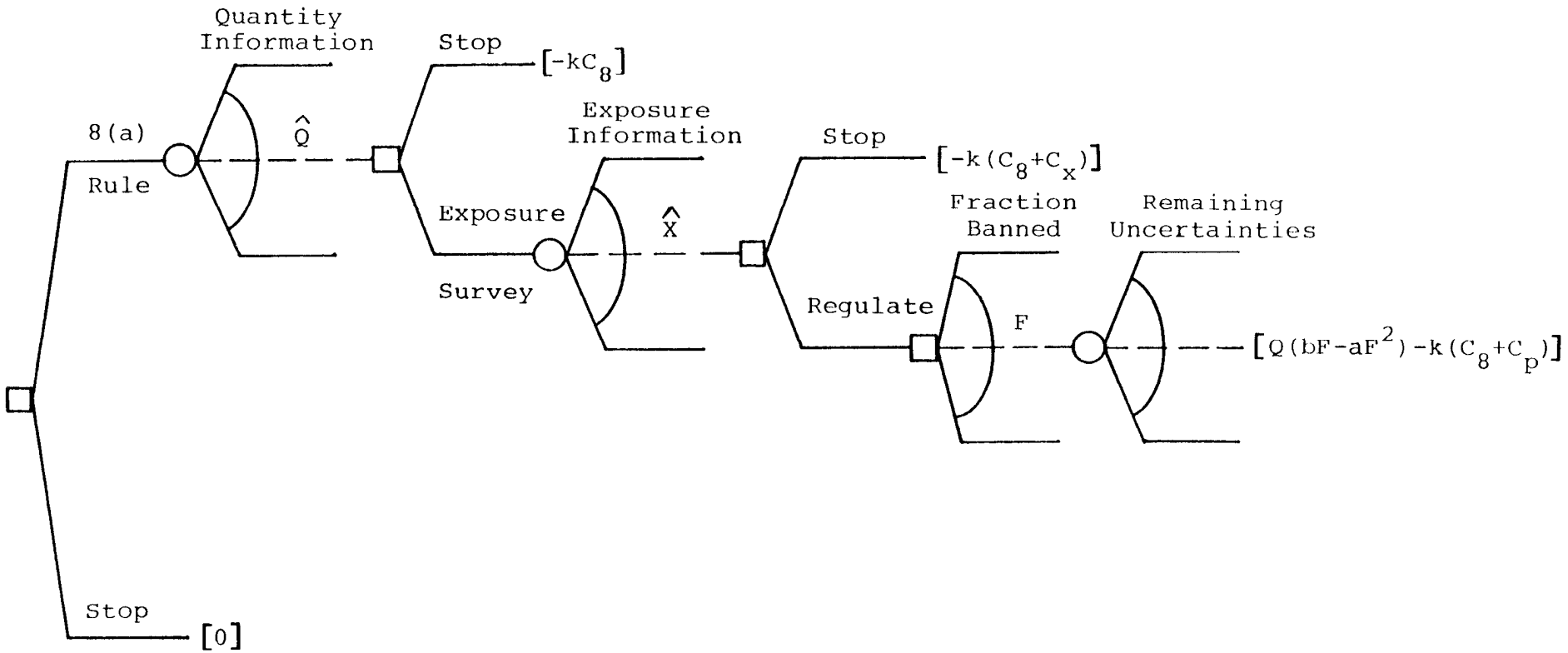

Figure 8. The Decision Tree Extended to Include Exposure Information

point, it must decide whether to stop, which yields a net benefit of $-k(C_8 + C_X)$, where C_X is the one-time cost of obtaining information on exposure. If EPA regulates, it must determine the stringency of control (F), as before. The remaining uncertainties are then resolved, yielding annual net benefits of $Q(bF - aF^2) - k(C_8 + C_P)$; note that because we assume that the cost of exposure information is included as part of the cost of promulgation, C_X does not appear in this expression.

To calculate the expected net benefits of the Section 8(a) strategy under this modified formulation, we need to estimate the cost of obtaining information on exposure (C_X) and our prior on what our estimate of b will be after the information has been gathered and analyzed. Officials at EPA estimated that an exposure study would cost approximately $250,000 to $500,000; we use the higher end of that range, C_X = $500,000, to allow for the costs of analyzing the results and making a decision whether or not to proceed.

Specifying how the information might affect our estimate of b is substantially more difficult. As we have stressed repeatedly, our estimate of b is highly uncertain. The information, however, affects only one source of that uncertainty -- it has no impact on the most uncertain component, the estimate of unit risk (R). Moreover, it will not provide perfect information on the exposure factor. Thus, we would not expect the information to lead to dramatic changes in our estimate of b.

To keep matters simple, let us assume that there are only two possible outcomes from the exposure study: it can indicate

that exposure levels are higher than expected, in which case the initial estimate of b is revised upward to b_H, or it can indicate lower exposure levels, in which case the estimate is revised downward to b_L. To simplify further, we assume that both possibilities are equally likely. For consistency, the average of b_H and b_L must be set equal to our initial mean estimate of b. For our base-case value of b = 0.5, that means that $(b_L+b_H)/2$ = 0.5, or $b_L = 1 - b_H$.

Table 8 shows the effect of varying b_H (and b_L) on the net benefits of the 8(a) branch. We show results both for the case of perfect information from the 8(a) rule (s^2 = 0.5) and for the more realistic case where the rule provides imperfect information on the quantity (s^2 = 0.25). Note that in the first line, with b_H = 0.5, the results are the same as under the earlier model; if the exposure studies do not affect the estimate of b, they do not have any impact on the value of the 8(a) branch. As b_H grows larger (and b_L smaller), the expected value of the 8(a) branch rises; the possibility of gathering additional information after revising the quantity estimate increases the value of the 8(a) rule. Note, however, that "Stop," with net benefits of 0, is still the preferred strategy unless the exposure studies are expected to result in a major revision in the estimate of b. Even with perfect quantity information (s^2 = 0.5), the exposure studies must lead to ±50 percent revision in the estimate of b (i.e., b_H = 0.75 and b_L = 0.25) for the 8(a) branch to have positive expected net benefits. With the more realistic assumption of s^2 = 0.25, reflecting the fact that the 8(a) information would still leave substantial uncertainty about the

Table 8. Net Benefits of 8(a) Rule When Benefit Information May Be Gathered Subsequently

	Net Benefits($1000/year)	
b_H	$s^2=0.5$	$s^2=0.25$
0.5	-20	-39
0.6	-18	-36
0.7	-5	-24
0.75	+5	-15
0.8	+17	-4
0.9	+43	+20

true value of Q, the exposure information must yield even more dramatic changes in the estimate of b for the 8(a) strategy to yield positive net benefits.

Benefit Information Provided by 8(a) Rule. The 8(a) rule might itself provide information that could be used to update our estimate of the unit benefit factor (b). Under the rule, firms would report on uses as well as volumes. As discussed in the previous chapter, exposure factors (particularly those for workers) are likely to vary widely across different uses. Thus, the average exposure factor (X) depends on the mix of uses and, at least in theory, could be updated with new information on what that mix is. We have not tried to quantify formally the link between the exposure factor and different types of dispersive uses, though we have a rough idea of the qualitative differences among exposure factors for different uses. We suspect, for example, that the exposure factor is higher for EDC used in paints and solvents than for EDC used to clean PVC reactors. Thus, if an 8(a) rule revealed that, contrary to expectations, a large proportion of EDC was used in paints and solvents, we might revise our estimate of X (and hence b) upwards. Conversely, if responses to the rule indicated that the only dispersive use of consequence was PVC reactor cleaning, we would revise it downwards.

Figure 9 illustrates how "extra" information from the 8(a) rule could be incorporated into the basic tree. The two initial choices are again "Stop" and issuing the 8(a) rule. As before, if we follow the 8(a) strategy, we resolve, at least partially,

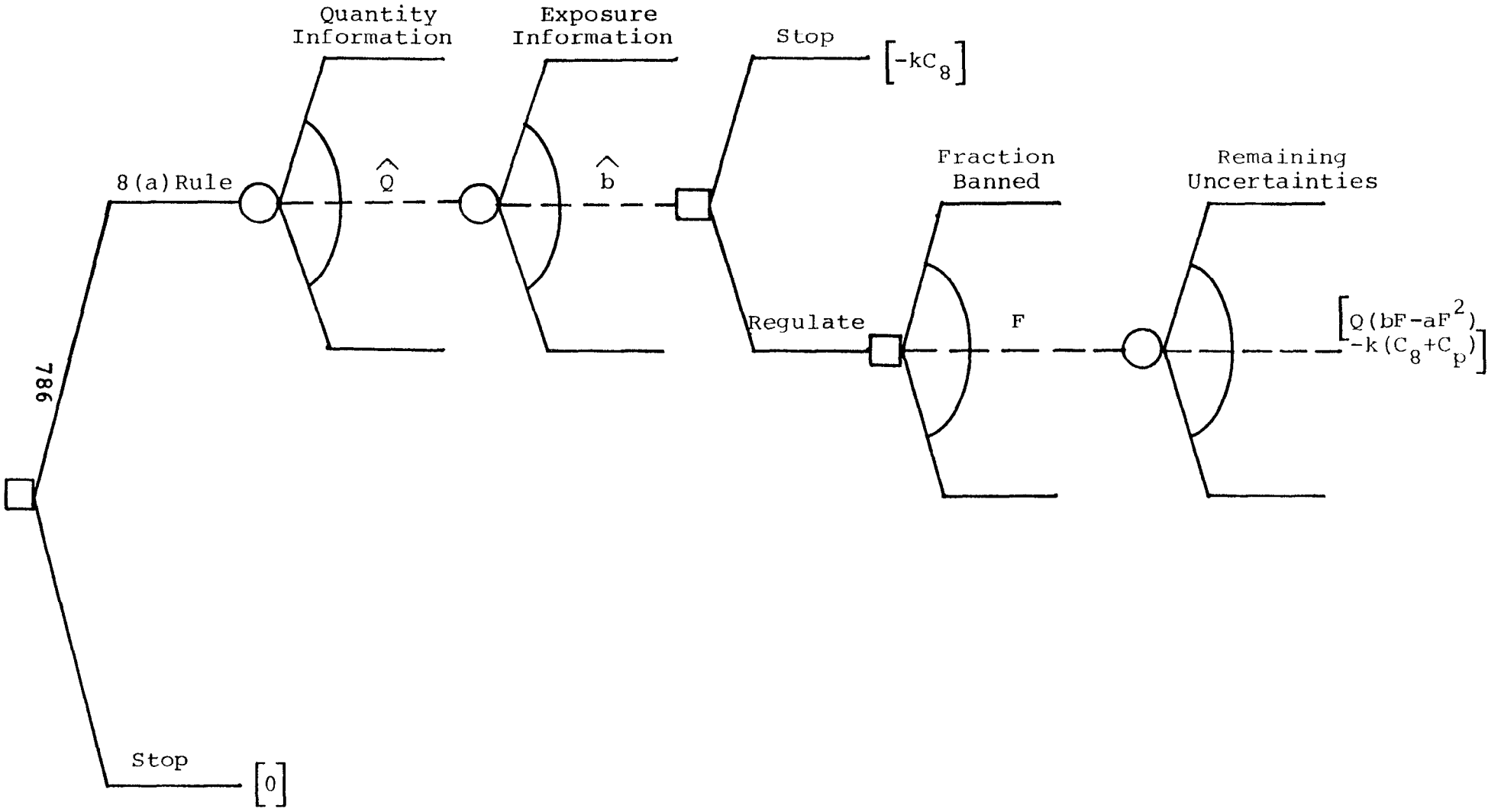

Figure 9. The Decision Tree Extended to Include Multiple Information from 8(a)Rule

uncertainty about the quantity. In this formulation, however, the rule also allows us to resolve some of the uncertainty about the unit benefit parameter (b) before having to decide whether or not to proceed with regulation.

For convenience, we assume again that the information results in either a high benefit estimate (b_H) or a low one (b_L), each with equal probability. Analytically, this model is equivlent to the one above with $c_X = 0$; the 8(a) rule provides some information on benefits at no additional cost. Table 9 reports the results. Note that even if it provides perfect information on the quantity ($s^2 = 0.5$), the 8(a) strategy fails to yield positive net benefits unless it also leads to a change of at least ±40 percent ($b_H = 0.7$) in the estimate of unit net benefits. Expected net benefits are substantially lower if the quantity information is imperfect ($s^2 = 0.25$). Thus, it appears that even if the 8(a) rule generates information on unit benefits as well the quantity, "Stop" is still the preferred choice.

Conclusions Regarding EDC

Our analysis suggests that the expected benefits of the information provided by the draft 8(a) rule would not exceed its costs, and thus, under the benefit-cost criterion, the 8(a) rule should not be promulgated. Many caveats must be attached to this conclusion, most based on the limited data available to estimate costs and benefits. Indeed, we are tempted to take refuge behind the usual disclaimers that this case study has been meant only for illustrative purposes, that a "real" analysis should seek out

Table 9. Net Benefits of 8(a) Rule When It Provides Information on Benefits and Quantity

	Net_Benefits($1000/year)	
b_H	$s^2=0.5$	$s^2=0.25$
0.5	-20	-39
0.6	-15	-33
0.7	+2	-17
0.75	+13	-6
0.8	+26	+5
0.9	+53	+33

better data, and so forth. We can point to many areas where we believe that with greater effort (and more resources) the analysis could be improved, though no matter how extensive the analysis, substantial uncertainties would remain because of the fundamental problems with estimating low-exposure risks. We also recognize, however, that analysis is itself a form of information gathering, and that calls for more analysis should receive the same kind of critical attention that any other proposal to expend resources to acquire information deserves. Indeed, had this been an actual decision, instead of a case study designed to illustrate some more general issues, we would have been inclined to terminate the analysis sooner rather than later.

The major basis for our conclusion is that dispersive uses of EDC appear to pose only a very small threat to public health, primarily because the volumes used are almost certainly small and declining. Although there is substantial uncertainty about how much EDC actually is used dispersively, we believe that the probability is very small that the volume is high enough to justify the substantial costs of promulgating a control regulation. Moreover, promulgation of a control regulation would draw limited Agency resources away from efforts to control other, potentially more serious environmental problems. EPA might wish to consider action short of banning certain uses or issuing emission control regulations, such as requirements for warning labels for products containing EDC. Such approaches probably would be easier and less costly to promulgate, though less certain to reduce risks. We have not investigated them in any detail, however, and thus are unable to make a recommendation.

VI. CONCLUSIONS AND RECOMMENDATIONS

The primary value of the case study lies not in the specific conclusions about dispersive uses of EDC, but rather in the more general insights it provides about the issues involved in estimating the value of Section 8(a) rules and, at a broader level, any information of potential use in making regulatory decisions about toxic substances. In this chapter, we summarize our conclusions, relating the specifics of the case study back to the broader issues raised in chapters 2 and 3.

The Role of Section 8(a)

Section 8(a) of TSCA allows EPA to promulgate rules requiring that firms submit information on substances being studied for potential regulation. The approach to information acquisition embodied in 8(a) has considerable intuitive appeal -- information is gathered directly from those most knowledgable about the substances and their uses, the manufacturers and processors. Thus far, however, only two significant 8(a) rules have been promulgated ("Level A" and asbestos), both in 1982 and both focusing on volume and use information.

Our analysis in Chapter 2 suggests several reasons why Section 8(a) might be used infrequently. The first problem is that use of 8(a) requires promulgation of a formal rule, with its attendant delays and costs. Thus, to be the preferred option, a Section 8(a) rule must offer significant advantages over alternative methods of acquiring the desired information.

Several EPA officials have indicated to us that they regard the 8(a) process as one that will be invoked only when no other means are available.

The second problem is that although 8(a) allows EPA to ask for several different types of information, its primary comparative advantage probably lies only in gathering volume and use data. Moreover, it seems likely that for most major use categories for large-volume chemicals, such data will be available from other sources. Thus, 8(a) is likely to be most applicable to small-volume chemicals, or to minor uses of high-volume chemicals (e.g., dispersive uses of EDC). But the benefits of information in many such cases may not be large enough to offset the substantial costs of promulgating an 8(a) rule.

Our analysis also suggests that 8(a) information may be much less accurate than one might expect from the fact that it places firms under a legal obligation to respond. As discussed in Chapter 2, we suspect that there may be substantial underreporting, particularly if EPA is unable to contact individual firms and must rely on the Federal Register and trade publications to inform firms of their responsibility to report. This problem is likely to be most severe precisely in those cases in which an 8(a) rule otherwise appears most desirable; that is, when little is known about the specific uses to which a chemical is put.

At this point it is difficult to estimate the magnitudes of these potential problems, in large part because final results

have not yet been received for the two most recent 8(a) rules that have been promulgated. We recommend that the results of those two experiences be studied carefully, both to learn more about the advantages and disadvantages of using Section 8(a), and to explore ways in which it might be used more effectively in the future.

The Use of Decision Analysis

Decision analysis provides a coherent conceptual framework in which to estimate the value of information gathered through a Section 8(a) rule or by other means. As the case study illustrates, however, the decision-analytic approach inevitably has a substantial subjective component; most parameters must be estimated with minimal data, and for some the only available source is the judgment of relevant officials. These problems arise, at least implicitly, in any effort to estimate the net benefits of toxic-substance regulation, but they are particularly acute in estimating the value of information at early stages of the regulatory process. As a result, the estimates of the value of information never are likely to be very firm.

The case study also illustrates, however, that even a crude decision analysis can provide useful insights. Much of the benefit comes simply from having to set up a benefit-cost framework as part of the process of performing the decision analysis. As we noted in Chapter 3, this can be an important discipline for decision makers, forcing them to think more closely about whether it makes sense to continue the regulatory process for a particular chemical or class of uses. Our base-

case calculations for EDC, for example, suggest that a total ban of dispersive uses would be unlikely to save even one life per year. Moreover, most of the benefits would be from reduced occupational exposure, suggesting that it might be more appropriate for OSHA rather than EPA to take the lead; OSHA, for example, could promulgate a new exposure limit that firms could meet in a variety of ways, including better ventilation and personal protection devices as well as substituting other chemicals.

In conjunction with the benefit-cost model, the decision-analytic framework plays an important role in forcing analysts to consider the liklihood of different parameter values, not just their possible range. Without the discipline of the decision-analytic framework, it is all to easy to gloss over uncertainties, or blindly to use "conservative" assumptions on the theory that it is better to over- rather than underestimate risks.

The need to make subjective probability estimates also is valuable because it forces one to think more carefully about the information already available, and to integrate qualitative and quantitative data. In the EDC case study, for example, our first reaction on reviewing the consultant reports was that very little was known about the amounts of EDC employed in dispersive uses. After more careful thought, spurred by the need to estimate a "prior" for the quantity, we were still uncertain about the precise quantity, but felt reasonably confident that it was "small." This assessment was based in part on the quantitative

estimates, but also on the qualitative information contained in the reports. As we noted in chapters 4 and 5, the difficulty that contractors had in finding individuals with direct knowledge of current dispersive uses of EDC (other than PVC reactor cleaning) was particularly suggestive.

Our case study was an analysis of a specific 8(a) rule that already had been drafted, presumably without the aid of decision analysis. It may be viewed as an example of the way in which decision analysis could be used to justify (or reject) the acquisition of specific pieces of information. As stated in Chapter 3, however, we believe that the major potential gains from decision analysis lie not in its use as a formal test, but rather in its integration into the decision-making process. It should be used to help generate information-gathering alternatives as well as to evaluate them. Formal decision analyses may be warranted when the stakes are large, or when parties outside EPA (such as OMB or the courts) require carefully documented evidence that the value of information exceeds its cost. Very crude, "back-of-the-envelope" decision analyses also can be very useful, however, in weeding out poor options and in defining better ones that deserve more careful consideration. Faced with many uncertainties, it is easy to conclude that almost any information would be useful. Often, however, a few quick, simple calculations can narrow the field considerably. They may show, for example, that even in extreme cases the information would not alter decisions. Such calculations also force decision makers to consider more carefully what they hope to learn from a particular piece of information, and may point to changes that

increase its potential value. These advantages of decision analysis are not limited to Section 8(a) rules, but rather apply to any significant decision about the acquisition of information.

Recommendations for Further Work

We have several concrete suggestions for further work to improve the usefulness of Section 8(a) rules and, more generally, decision analysis in the regulatory process. First, as mentioned above, we suggest that EPA carefully monitor the information-gathering process now underway for two Section 8(a) rules. Much of our analysis in the EDC case study assumed that the Agency would receive accurate information from an 8(a) rule. We found that taking into account the fact that the actual information would be imperfect substantially reduced the value of the rule. EPA's experiences to date with the asbestos 8(a) rule suggest several ways in which accuracy could be improved. A detailed study could provide important insights.

Second, we think that it would be useful to apply the decision-analytic framework to a regulatory decision currently in progress, as opposed to one that already has been made (as was the case for our study of EDC). We are not advocating another case study, but rather a "trial run" that directly involves the EPA officials responsible for formulating the regulatory options and deciding what information to gather. Such involvement would be important both to gain a better idea of the practical problems of using decision analysis and to acquaint officials with its potential usefulness.

Finally, our experience with the case study suggests that it would be useful to develop some "generic" estimates of parameter values that are common to many decisions. We have in mind, for example, some standard estimates of exposure factors for different classes of substances and uses. Although it may be necessary to do detailed exposure studies before a final regulation is proposed, rough "general" estimates would be very useful in performing analyses at earlier stages. Given the importance of promulgation costs in our analysis, we also suggest that an effort be made to develop better estimates of those costs, both to EPA and to outside parties. Having a set of standard estimates for these parameters, and others, would facilitate the use of decision analysis, and also help ensure greater consistency across decisions.

NOTES

1. Although we focus on expected net benefits, decision analysis also may be applied to other objective functions. In decision analyses of financial decisions, for example, frequently dollar amounts are expressed in terms of utility, to account for risk aversion (Raiffa 1968).

2. Unless otherwise noted, information on the asbestos rulemaking was obtained in interviews with Rick McAllister and Amy Moll of the U.S. EPA, Washington, D.C.

3. We follow the convention that the status quo of "No Ban" is defined as having zero net benefits. Thus, uncertainty about exposure translates into uncertainty about the benefits of banning. An alternative that yields identical conclusion is to look at the net social costs of each alternative. In that case we would be certain about the cost of banning, but uncertain about the cost (health risk) of not banning. So long as the decision criterion is to pick the option with the highest expected net benefits (or the lowest expected net costs), it does not matter which formulation is used.

4. The conversion is straightforward. First convert to ppbs by dividing by 4.1:

   $C_{ppb} = (225Q/u)/4.1 = 54.9Q/u.$

   As there are 31,557,600 seconds in a year (based on 365.25 days per year), an emission rate of 1 gram per second per square km is equivalent to annual emissions of 31,557.6 kg per square km. Thus one kg of emissions causes an annual average concentration of $(54.9/u)31,557.6 = 1.74 \times 10^{-3}/u$ ppb over 1 square km. We then multiply by the number of people, D, living in that square km to get the total level of exposure.

5. Given our assumption that all units of emissions cause the same amount of exposure, this is the correct order in which to eliminate dispersive uses. In reality, of course, different uses are likely to have different exposure factors. The correct procedure then is to ban in order of the ratio of cost to exposure factor. For more discussion of this issue, see Nichols (forthcoming).

6. The debate over the appropriate rate of discount to use for projects such as this is voluminous and inconclusive, with suggestions ranging from near zero to 10 percent or more. Our choice of 5 percent represents an uneasy compromise between these extremes.

7. A "Basic" computer program has been developed to perform the necessary calculations. Its computational strategy, in brief, is to calculate the critical value(s) of Q and then to compute the probabilities and conditional expectations of Q using numerical integration. Interested readers may obtain a copy of the program from the authors.

8. With the log-normal distribution, varying s^2 also changes E(Q), as $E(Q) = \exp(u + s^2/2)$. To hold E(Q) constant, as we varied s^2, we also varied u by setting $u = \ln[E(Q)] - s^2/2$.

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